Firm dynamics in an global and uncertain economy

Gigout, Timothee

Collège de France, Université de Lille

3 September 2019

UNIVERSITÉ DE LILLE

ÉCOLE DOCTORALE DES SCIENCES ÉCONOMIQUES
SOCIALES, DE L'AMÉNAGEMENT ET DU MANAGEMENT

UMR 8019 - Centre lillois d'études et de recherches
sociologiques et économiques

Thèse présentée pour obtenir le grade universitaire de Docteur

Discipline: Sciences Humaines
Spécialité: Économie

Timothée Gigout

Firm dynamics in an global and uncertain economy

Sous la direction de Fabien Tripier

Soutenance le 02/10/2019 devant le jury composé de:

M. Jean Imbs, Professeur à l'École d'Économie de Paris	Rapporteur
MME. Isabelle Méjean, Professeur à l'École Polytechnique	Rapporteur
M. Philippe Aghion, Professeur au Collège de France	Examinateur
M. Matthieu Bussière, Directeur DEMFI - Banque de France	Examinateur
M. Jérome Héricourt, Professeur à l'Université de Lille	Examinateur
M. Fabien Tripier, Professeur à l'Université d'Evry	Directeur de thèse

Contents

Remerciement

Je remercie en premier lieu mon directeur de thèse Fabien Tripier. Cette thèse doit beaucoup à la capacité de Fabien à arbitrer avec sagesse et réalisme entre son rôle de directeur de thèse et celui de co-auteur.

Je tiens aussi à exprimer ma gratitude à Isabelle Méjean, Jean Imbs, Jérôme Hericourt, Matthieu Bussière et Philippe Aghion pour avoir accepté de faire partie de mon jury de thèse et pour le temps qu'ils ont contribués afin de me permettre d'améliorer la qualité de ce manuscrit.

Je souhaite par ailleurs remercier toutes les personnes qui m'ont soutenues durant toutes ces années d'études en économie: Daniel Mirza pour m'avoir donné le goût de la recherche, Jean-Charles Bricongne qui m'a offert l'opportunité de rejoindre les équipes de recherche de la Banque de France, ainsi que de nombreuses personnes au sein de cette institution pour leurs précieux conseils et encouragements tout au long de ma thèse, au premier rang desquels Clément, Antonin, Simon et les CIFRE. Je dois beaucoup de mes progrès réalisés cette dernière année aux membres de la Chaire d'économie du Collège de France.

Last but not least, je remercie du fond du cœur mes parents pour leur soutient sans faille, leur patience inégalable et leur confiance en moi tout au long de cette longue aventure.

Résumé / Abstract

Cette thèse a pour objet l'étude de la dynamique des entreprises en économie ouverte en présence d'incertitude. Dans un premier chapitre, je mets en évidence les effets réallocatifs de l'incertitude sur les investissements directs à l'étranger des multinationales Françaises. Dans un second chapitre, je montre qu'une augmentation de l'incertitude de la demande à un effet négatif sur la croissance des entreprises et que sa persistance dépend du degré de synchronisation de la firme avec son secteur. Enfin, dans un dernier chapitre j'illustre comment la marge extensive du commerce international contribue à façonner la direction, la quantité et le contenu de la transmission des connaissances technologiques entre entreprises de pays différents.

In this dissertation, I study firm dynamics in the context of a global and uncertain economy. In the first chapter, I show how uncertainty generates reallocation among French multinationals. In a second chapter, I study how an increase in demand uncertainty negatively impacts firm growth and how the persistence of this effect depends on the synchronicity of the firm dynamic with that of the other firms in its sector. Finally in the third chapter, I highlight how the extensive margin of international trade contribute to shape the direction, quantity and content of the international transmission of knowledge.

Chapter 1

Introduction

Les entreprises évoluent dans un environnement mondialisé et incertain. Ces deux éléments sont un thème récurrent des débats économiques, en particulier quand les conditions se dégradent. C'est à ce moment que s'intensifient les interrogations sur les interactions entre d'une part le devenir des agents économiques, entreprises ou individus, et d'autre part la nature de leurs expositions au reste du monde. Les trois chapitres de cette thèse ont pour thème commun d'identifier comment l'incertitude et les liens internationaux sont affectés, et en retour, affectent la dynamique des entreprises. La dynamique des entreprises est au cœur de ces trois chapitres grâce à l'utilisation de données désagrégés décrivant leur investissement domestique et étranger, leur commerce ou encore leur innovation.

Dans un premier chapitre, co-écrit avec Raffael Cezar et Fabien Tripier, nous étudions l'impact de l'incertitude sur les investissements transfrontaliers. Nous construisons une base de données de flux et stocks d'Investissements Directs à l'Étranger entre des multinationales Françaises et leurs filiales à l'étranger pendant les années 2000 à 2015. Nous créons une mesure de l'incertitude basée sur la dispersion des rendements idiosyncratiques des investissements. Cette mesure varie par pays et années. Nous trouvons qu'une augmentation de cette mesure cause un ralentissement des investissements vers les destinations touchées. Cependant cet effet est fortement hétérogènes selon les caractéristiques des multinationales concernées. Les entreprises dont la performance avant l'augmentation était faible diminuent fortement et durablement leur investissement. Les entreprises relativement plus performantes tendent au contraire à augmenter leur investissement dans une proportion plus élevée qu'elles ne l'ont réduite l'année du choc. Nous interprétons ces résultats comme indicatif de la présence d'un effet de ré-allocation entre multinationales causé par l'incertitude.

Dans le deuxième chapitre, écrit en collaboration avec Jean-Charles Bricongne, nous étudions l'effet de l'incertitude sur la croissance domestique des entreprises. Nous utilisons des données de commerce international désagrégées pour calculer une mesure exogènes de l'incertitude des chocs de demande à laquelle chaque entreprise doit faire face. Nous l'apparions avec des données fiscales et douanières qui recouvrent les entreprises concernées de manière quasi exhaustive durant la période 1996-2013. Un accroissement de l'incertitude cause une baisse persistante de la croissance de l'emploi et de l'investissement des firmes concernées. Si l'effet contemporain négatif peut s'expliquer grâce à la théorie des options réelles, sa persistance suggère la coexistence d'un autre mécanisme. Nous montrons que cette persistance s'explique an grande partie par l'interaction de l'incertitude avec des effets de compétitions.

Enfin dans le troisième chapitre, co-écrit avec Philippe Aghion, Antonin Bergeaud, Marc Melitz et Matthieu Lequien, nous nous intéressons à la transmission internationale des connaissances via le canal du commerce. Lorsqu'une entreprise commence à exporter dans une nouvelle destination, ses produits et ses technologies deviennent soudainement visibles. Les entreprises de cette destination peuvent alors mettre à profit les découvertes de l'entreprise étrangère pour à son tour générer de l'innovation. Nous combinons des données administratives et douanières Françaises ainsi que des données de brevets recouvrant la période 1995-2012. Nous montrons que l'entrée dans un nouveau marché d'exportation augmente le nombre de citations provenant de cette destination. Ces effets de débordement technologiques sont concentrés dans les pays à niveau de développement intermédiaires et sur les brevets des entreprises les plus productives.

La contribution commune de ces trois chapitres est d'avoir fait avancer l'état des connaissances dans le domaine de la transmission internationale des chocs via les liens directs entre entreprises. Les deux premiers, portant sur l'incertitude, ont isolé l'effet de l'incertitude sur l'allocation des ressources dans l'économie entre entreprises opérants dans un même secteur. Le troisième a illustré comment la marge extensive du commerce international contribuait à façonner la direction, la quantité et le contenu de la transmission des connaissances technologiques entre entreprises de pays différents.

Chapter 2

Cross-border Investments and Uncertainty: Firm-level Evidence of a Reallocative Effect

In collaboration with Rafael Cezar & Fabien Tripier

1 Introduction

"Brexit fear hits foreign direct investment." Financial Times, 2016

"This uncertainty on where we are going in regards to trade policy and Nafta has put some international investment in a holding pattern." C. Camacho, President and CEO of the Greater Phoenix Economic Council. Financial Times, 2017

Foreign investors fear uncertainty. This widespread view is repeatedly invoked in the media and political circles during turbulent times as in the current context of Brexit and trade wars. In this paper, we build a measure of uncertainty based on FDI returns of French Multinational Firms (MNF or firms hereafter) to document how FDI react to a rise in uncertainty of FDI returns in the host country. A striking result of our empirical analysis is the great heterogeneity of the effect of return uncertainty on FDI decision. A slightly negative and short-lived *average* effect hides a strong negative and persistent effect for low-performing MNF which turns out to be positive for high-performing ones. Therefore, besides its moderate effects on average, FDI uncertainty appears as a key driver of reallocation of foreign direct investments between MNF.

The starting point of our paper, and our first contribution to the literature, is to build a micro-data based measure of uncertainty for FDI returns. While investigations on the impact of uncertainty on FDI in the literature rely upon global measures of uncertainty as the electoral cycle (e.g. Julio and Yook (2016)), the stock market volatility (e.g. Gourio et al. (2016)) or the exchange rate uncertainty (e.g. Jeanneret (2016)), we investigate herein a measure of uncertainty which is specific to FDI. Our measure presents the advantage of being more directly connected with the FDI's decision. To build this measure, we construct a novel affiliate-level data-set of French outward FDI flows and assets abroad.[1] This data-set allows us to compute the entire distribution of FDI returns for almost all French MNF over the 2000-2015 sample period.

The standard deviation of FDI returns distribution is informative about the realized risk of FDI, but it cannot be used directly as a measure of exogenous FDI uncertainty. As emphasized by Bloom (2014), exogenous fluctuations in uncertainty are not directly observable and

[1] Vicard (2018) also uses the Banque de France databases to measure FDI returns to study the role of corporate tax avoidance.

we therefore have to rely on necessarily imperfect proxies. By looking at the width of the distribution of the reasonably unpredictable component of those outcomes, we get closer to the true notion of uncertainty as Jurado et al. (2015) point out. To get a more accurate measure of uncertainty, we then consider the dispersion of FDI returns which are not predicted by relevant factors. The selected factors are borrowed from the literature in finance on idiosyncratic volatility of returns. Whereas Ang et al. (2006) and Ang et al. (2009) use a multiple French and Fama Factors model to predict idiosyncratic returns, it is also possible to employ a more parsimonious model as in Anderson et al. (2009) and Boutchkova et al. (2012). In that set-up, firms' returns are typically regressed over two indexes of country and global returns with some fixed effects accounting for firm invariant characteristics. We also borrow to the literature on uncertainty measures based on firm-level data exposed in Bloom (2014) and more precisely Bloom et al. (2018) who apply auto-regressive models to the establishment-level measure of productivity to identify uncertainty shocks on firm productivity. Therefore, our measure of uncertainty is defined as the standard deviation of the component of FDI returns which is unexplained by the lagged value of FDI returns, the indexes of world and country FDI returns, and an estimated structure of fixed effects.

Our measure of uncertainty is time-varying with cross-country and cross-sectoral dimensions.[2] The highest uncertainty is observed in 2008 in Thailand, a year marked by a very serious political crisis.[3] We also observe high values during the Great Recession for several emerging countries (South Africa, India and Romania) and the famous 2001 financial crises in Argentina and Turkey, as well as in Russia (in 2002 and 2006, a year of tensions with Ukraine and international sanctions). Our measurement is therefore a synthetic indicator of the several dimensions of uncertainty (economic, political and financial).

We then estimate how FDI react to uncertainty by regressing the individual FDI outflows by French MNF on our measure of uncertainty together with a set of relevant control variables and

[2]We do not find any effect of sectoral uncertainty, so we focus herein on the consequences of host-country uncertainty.

[3]The ranking of values above 30 (the average is 18.03) is as follows: Thailand (2008) 35.06, South Africa (2007) 33.92, India (2008) 33.74, Argentina (2001) 33.38, Romania (2008) 31.93, Russia 2002 (31.61053), Russia (2006) 30.27. Turkey (2001) 30.84.

fixed effects. We supplement our results with the Local Projection method of Jordà (2005) to assess the persistence of the adverse effect of uncertainty on FDI.[4] Following a one interquartile range increase in uncertainty in one country, French MNF decrease the rate of their direct investments to the affected country by as much as 0.904 points of percentage. Using split-sample analysis, we show that this figure hides a strong heterogeneity among MNF. Parent companies with low ex-ante performance bear the brunt of the losses from uncertainty and do not experience any recovery in the following years contrary to parent companies with high ex-ante performance. Indeed, the fall of 0.904 points of percentage of FDI growth on average is associated with a gap of 5.98 points of percentage three years after between parent companies with the highest and the lowest ex-ante performance. In fact, the rise in uncertainty has a positive effect for high-performing parent companies (2.60 ppt) while low-performing firms experienced a dramatic fall in FDI (-3.38 ppt). The small and short-living average effect hides strong and persistent heterogeneous effects of uncertainty on FDI.

We propose an illustrative model to explain the effect of uncertainty shocks on foreign investments and to account for heterogeneous responses of multinational firms. The model is based on the costly-state verification setup originally developed by Townsend (1979) and Bernanke et al. (1999) extended by Christiano et al. (2014) to make uncertainty time-varying as the outcome of "Risk shocks". An increase in uncertainty leads to a fall in investment by foreign investors who support an increase in external finance costs as a consequence of the increase in risk in the destination country. In the context of firm heterogeneity, with respect to the importance of costly-state verification, we observe however an increase of investment by foreign investors with low verification costs who get back market shares from those with high verification costs.

Our results contribute to the large literature on the relation between FDI and uncertainty. This literature has emerged after the collapse of Bretton-Woods agreements with a focus on the choice by MNF between investments or exports to serve foreign markets in the new context

[4]The use of local projections has recently been introduced for micro data where they provide a parsimonious and tractable alternative to VAR models to compute impulse response functions in the presence of potential non-linearities – see Favara and Imbs (2015) and Crouzet et al. (2017).

of floating exchange rates – see Helpman et al. (2004) for a seminal contribution on this topic and Fillat and Garetto (2015) for a treatment of this choice under uncertainty. Theoretical and empirical results have been provided to support either a positive impact of exchange rate uncertainty on FDI (Fernández-Arias and Hausmann, 2001; Cushman, 1985; Goldberg and Kolstad, 1995) or a negative impact (Aizenman and Marion, 2004; Ramondo et al., 2013; Lewis, 2014) – and even more recently a non-linear relationship in Jeanneret (2016), which is negative for low uncertainty levels and positive otherwise.[5] The complexity of the FDI–uncertainty relation has been reinforced by the evidence on the important role of another source of uncertainty, namely political uncertainty, in shaping foreign investment (Rodrik, 1991; Julio and Yook, 2016). Our results confirm the importance of the effect of uncertainty not only on the aggregate level of FDI flows, but also on the composition of the MNF at the origin of those flows. Moreover, the great heterogeneity of uncertainty effects highlighted in this paper may explain the difficulty in this literature to reach a clear cut conclusion on the FDI-uncertainty relation.

Our results contribute also to literature on the heterogeneous effects of uncertainty shocks. Heterogeneity was identified in the earlier studies on investment dynamics: the negative impact of uncertainty on investment is much greater in industries dominated by smaller firms in Ghosal and Loungani (2000), in more concentrated sectors in Patnaik (2016) and for firms with substantial market power in Guiso and Parigi (1999). More recently, Barrero et al. (2017) finds that more financially constrained firms drive most of the negative effect of uncertainty on firm domestic growth. For trade, Handley and Limao (2015) and Handley and Limão (2017) demonstrate the importance of firm heterogeneity to quantify the consequence of trade policy uncertainty in the context of Portugal accession to European community and the China's WTO accession, respectively. De Sousa et al. (2018) find that more productive firms are more affected by expenditure volatility in the destination country while Héricourt and Nedoncelle (2018) show that multi-destination firms loose market share to mono-destination ones. Our contribution is to extend this set of results to FDI and to identify the role of returns as a key source of heterogeneous responses of firms to uncertainty.

[5] See Table 2 in Russ (2012) for a synthetic review of these results.

Finally, it is worth emphasizing that heterogeneity concerns the sign of the impact and not only its magnitude: the impact of uncertainty is positive for high performing firms. It is interesting to mention that such a stimulating effect of uncertainty on investment has also been identified for R&D by Atanassov et al. (2018) and Stein and Stone (2013). Similarly, Mohn and Misund (2009) conclude that uncertainty has a stimulating effect on investment in oil and gas sectors and Marmer and Slade (2018) show that greater uncertainty encourages the opening of new mines for the U.S. copper mining market. The authors explain this result by the timing of these specific investments; consistently with Bar-Ilan and Strange (1996) who show that investment lags reverse the standard result of the literature on adverse effects of uncertainty on investment surveyed by Dixit (1992) and Pindyck (1991). FDI may share some features with these types of investment which would explain why they react positively with uncertainty for the most performing firms in our sample.

The remainder of the paper is organized as follows. Section 2 describes the construction of our novel affiliate-level data-set of French outward FDI flows and assets abroad and detail the methodology used to compute an uncertainty proxy based on the dispersion of the idiosyncratic performance of French Multinational Firms (MNF). Section 3 provides our empirical results concerning the effects of uncertainty on FDI and Section 4 a set of robustness tests. The model is presented and simulated in the Section B of the Appendix. Section 5 concludes.

2 Data

This section presents the data and the methodology to construct the measure of uncertainty.

2.1 Direct Investment Assets and Income data

Our data on Foreign Direct Investments come from highly disaggregated data available at the Banque de France. Those databases are provided by the Direct Investment Unit of the Statistical General Directorate with the primary goal of producing and publishing each year the Balance of Payment and International Investment Position.

Most of the information is obtained from an annual survey performed by the regional branches of the Banque de France. It covers French companies with assets, in France or abroad over €10M, and a direct financial link (at least 10 % of the invested firm's capital) to at least one foreign company. The parent company then has to report assets for every subsidiary for which it owns more than €5M in capital or whose acquisition cost was greater than €5M. The Direct Investment Service estimates that the uncollected data below the threshold represent less than 0.5 % of total stocks. In addition to this annual survey, the parent company must systematically report flows to and from its affiliate no later than 20 days after each transaction. We discard Direct Investment debt and cash instruments, for which income data became available only in 2012, to consider only investment in equity capital.[6]

This process generates two separate databases for flows and assets, each with a slightly different level of granularity and without an explicit identifier for the affiliates abroad. To merge them together, we match any flows and assets from a given French parent company into a given sector-country as if they belonged to the same national foreign affiliate. Sectors are defined using the 4-digit NAF code. Holdings are assigned, whenever available, the NAF equivalent of their Industrial Classification Benchmark (ICB).

To compute our measure of dispersion, we restrict the sample to countries where at least 15 French MNF are active every year. We do so to reduce the influence of potential outliers when computing the standard-deviations. The final data-set includes over 41000 observations in 38 countries between 2000 and 2015. On average, we follow about 1300 French parent companies and 3800 affiliates every year.

2.2 Direct Investment Returns

Thereafter, the letter $t = \{1, ..., T\}$ corresponds to the year, the letter $s = \{1, ..., S\}$ to the French parent firm, the letter $j = \{1, ..., J\}$ to the country, and the letter $k = \{1, ..., K\}$ to the sector. The

[6]Moreover, Blanchard and Acalin (2016) detail the strong correlation between the flows of FDI coming in and out of a country. They show that this high correlation represents flows that are just passing through rather than the acquisition of a lasting interest in a resident enterprise according to the IMF definition of a FDI. Focusing only on equity flows should give us a better measure of MNFs exposure to country-specific uncertainty.

intersection of those last three groups is the affiliate indexed with the letter $a = \{s, j, k\}$ – since there is a single affiliate a of the parent s in the country j and the sector k.

In order to build our measure of uncertainty, we compute the Returns On Investment (ROI, hereafter) of the foreign affiliates of French firms. We use the income paid (I, hereafter) by the affiliate a to its parent company in year t. We include both dividends paid to the parent company and earnings re-invested into the affiliate (D42 and D43 in the System of National Account 2008 respectively). We normalize the income over the amount of equity invested into the affiliate by the parent company up to year $(t-1)$:

$$ROI_{a,t} = \frac{I_{a,t}}{COF_{a,t-1}} \tag{1}$$

where the denominator COF stands for the Cumulative sum of Out-Flows from the parent firm to its affiliate, which is itself constructed as follows:

$$COF_{a,t} = FA_{a,0} + \sum_{\tau=1}^{t} NOF_{a,\tau} \tag{2}$$

where $FA_{a,0}$ corresponds to the initial market value of the stock of equity of affiliate a, i.e. the *Financial Assets*, and $NOF_{a,\tau}$ to the Net Out-Flows as of time τ. Those variables includes all equity labeled with an F511 or F512 SNA2008 code (acquisition of equity, listed and unlisted respectively). $NOF_{a,\tau}$ also includes disinvestment & repatriation that appear as a negative FDI flow. The market value of equity is used only to get the initial value of the stock. Any fluctuations in COF originates from changes in FDI decisions by the parent firm and not in valuation effects. Finally, we exclude cases of negative assets and non plausible rate of returns, which are any rates below -100% and above 100%.[7] Table 1 provides summary statistics of our database.

[7]This threshold also happens to be in line with the most common practice in the finance literature. For example, the threshold is 25% in Morck et al. (2000), 75% in Boutchkova et al. (2012), and 200% in Dang et al. (2015).

Table 1: Summary Statistics

	N	Mean	Median	Std.Dev.
Panel A Affiliate-level				
Affiliate Assets$_{a,t}$ (Mn.)	55021	180.47	15.65	1009.58
Affiliate Flows$_{a,t}$ (Mn.)	55021	8.30	0.17	229.08
$ROI_{a,t}$ (%)	55021	9.90	5.23	24.66
Δ COF$_{a,t}$ $\times$ 100	49869	3.37	2.15	45.40
Panel B Firm-level				
Affiliates per firm	19387	2.97	2.00	3.43
Parent Firm Assets$_{s,k,t}$ (Mn.)	19387	521.94	37.31	2567.50
Parent Firm Flows$_{s,k,t}$ (Mn.)	19387	33.00	0.66	426.55
Panel C Country-level				
Affilates per country	570	102.48	62.00	95.57
French Assets$_{j,t}$ (Bn.)	570	17.89	3.92	33.19
French Flows$_{j,t}$ (Bn.)	570	1.26	0.29	3.54
Panel D Year-level				
Affilates per year	15	3894.27	3782.00	909.63
French Assets$_t$ (Bn.)	15	679.83	688.85	210.41
French Flows$_t$ (Bn.)	15	47.83	48.42	16.39

NOTE: Banque de France FDI databases, authors' computation. Mn. indicates millions of Euros and Bn. billions of euros.

2.3 Measuring Uncertainty on FDI Return

Our estimate of uncertainty is based on the following two-step procedure. The first step consists in removing the forecastable component of the variation of affiliates' returns. The forecasting model of returns merge the portfolio approach of Boutchkova et al. (2012) for returns and the methodology implemented by Bloom et al. (2018) for productivity. We break returns into a first component explained by a set of regressors and a second unexplained component, the residuals, as follows

$$ROI_{a,t} = \gamma_1 ROI_{a,t-1} + \gamma_2 ROI_t + \gamma_3 ROI_{j,t} + \gamma_j \times \gamma_k + \gamma_s + u_{a,t} \tag{3}$$

where $ROI_{a,t}$ is the yearly return of affiliate $a = \{s, j, k\}$ as of time t; $\gamma_j \times \gamma_k$ capture time invariant country-sector specific heterogeneity while γ_s capture firm characteristics of the parent company. The variables ROI_t and $ROI_{j,t}$ are, respectively, the average world and country$-j$

returns of French MNF in period t. We compute them as follows:

$$ROI_t = \frac{1}{A_{t,\backslash a}} \sum_{a_i \neq a}^{A_{\backslash a}} ROI_{a,t}, \tag{4}$$

and

$$ROI_{j,t} = \frac{1}{A_{j,t,\backslash a}} \sum_{a_i \neq a; a \in j}^{A_{j,t,\backslash a}} ROI_{a,t} \tag{5}$$

where A_t and $A_{j,t}$ are counters for the total number of affiliates in year t and country j in year t, respectively. We exclude the observation corresponding to the affiliate from the computation of its market returns. We present the results of this first stage, equation (3), in Table 2. As expected, returns are persistent (the coefficient of lagged returns is equal to 0.330 and significantly different form zero) and highly correlated with the aggregate country and world returns. The systematic component explains 28% of the variance of returns. We interpret the residuals as the idiosyncratic returns (Boutchkova et al., 2012).

Table 2: 1st Stage Results

	$ROI_{a,t}$ (%)
$ROI_{a,t-1}$ (%)	0.330***
	(0.00)
Country average ROI	0.277***
	(0.00)
World average ROI	0.252***
	(0.00)
Sector X Country FE	Yes
Parent Firm FE	Yes
Observations	44018
Adjusted R^2	0.283

p statistics in parentheses, with robust SE.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In the second step, we calculate the country-specific moments of French affiliates idiosyncratic returns as follows:

$$\texttt{MEAN}_{j,t} = \frac{1}{A_{j,t}} \sum_{a \in j}^{A} \hat{u}_{a,t} \tag{6}$$

where $\hat{u}_{a,t}$ denotes the residuals from the estimation of equation (3), and

$$\mathtt{DISP}_{j,t} = \left[\frac{1}{A_{j,t} - 1} \times \sum_{a \in j}^{A} (\hat{u}_{a,t} - \mathtt{MEAN}_{j,t})^2 \right]^{1/2} \tag{7}$$

where $\mathtt{DISP}_{j,t}$ measures the dispersion of the residuals, e.g. how widely uninformative fundamentals are to predict firm specific returns. Throughout this paper, we will use $\mathtt{DISP}_{j,t}$ as our proxy for time varying uncertainty over the idiosyncratic returns of French MNF in country j.

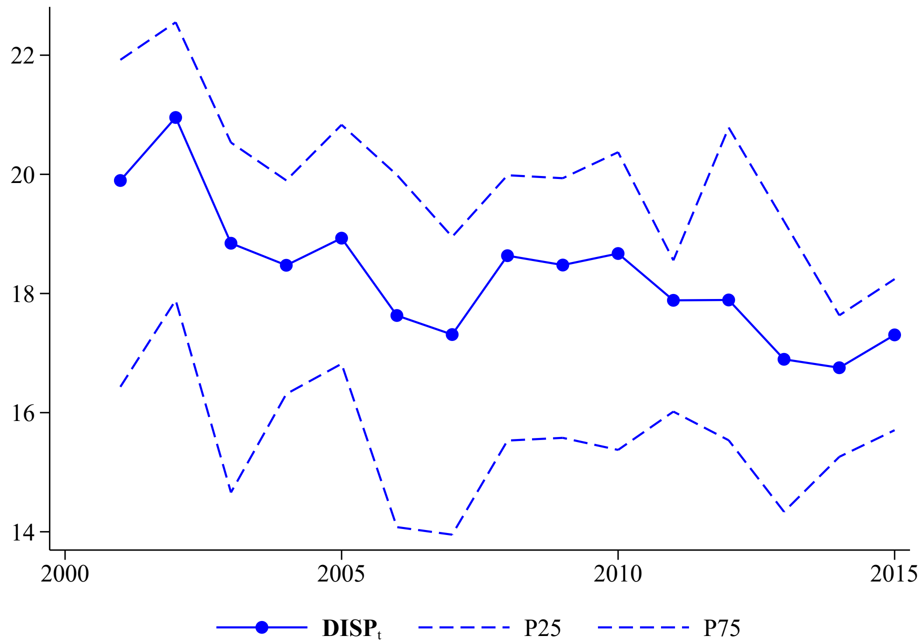
2.4 Stylized Facts

The mean value of the uncertainty is 18.04 for the panel of 570 year-country observations, but it varies substantially across time, countries, and sectors. Figure 1 shows the mean value of FDI uncertainty for each year between 2001 and 2015. Uncertainty has declined from 2002 to 2007, just before the financial crisis, and then increased between 2008 and 2009. Afterwards, it has decreased once again to recover the pre-crisis level. This pattern is close to that of the VIX[8], but with notable differences (Figure A.1 in the appendix compares the two measures). Besides, the interest of our measure of uncertainty is to vary across countries and sectors contrary to the VIX index.

Dispersion across countries is quite large – the mean value of uncertainty by country is reported in Table 3. It varies from 12.79 in Tunisia to 22.21 in Russia. Interestingly, the dispersion does not seem related with the level of development. Uncertainty is high in some emerging economies as Russia (but also in Romania or India), as we should expect, but very low in Tunisia (but also in Thailand or South Korea). Actually, we do not find a significant correlation between uncertainty and the real GDP per capita in our data. It is worth mentioning, that we are not considering here the variance of realized returns but the variance of the idiosyncratic component of returns after we control for country average returns and country(-sector) fixed effects – see equation (3).

[8]The VIX is the implied volatility on the US stock market and is widely used as a worldwide measure of uncertainty.

Figure 1: FDI Return Uncertainty



NOTE: This figure presents the time-varying distribution of our measure of return uncertainty. $\mathtt{DISP}_t$ is the average of all $\mathtt{DISP}_{j,t}$ which is defined by equation (7).

Figure A.3 shows that the orthogonalization procedure was successful. The second moment of the idiosyncratic performance shocks is less correlated with country fundamental economic characteristics than the second moment of the raw returns. It validates the use of $\mathtt{DISP}_{j,t}$ as an exogenous source of uncertainty that we can causally identify.[9]

[9]Moreover, if we omit this procedure, the response function of FDI to the dispersion of the raw returns exhibits some evidence of pre-trend issue.

Table 3: FDI Return Uncertainty

	Affiliate-Year	Return Uncertainty	P25	P75
ARG	664	18.44	13.07	24.71
AUS	987	18.84	16.71	20.93
AUT	591	18.19	14.56	21.34
BEL	4050	16.15	13.92	18.04
BRA	1602	19.00	16.41	21.41
CAN	1450	16.34	14.23	17.91
CHE	2302	18.72	16.83	20.59
CHN	1573	19.18	17.45	20.27
CIV	405	15.91	13.15	17.09
CZE	959	19.17	15.53	24.67
DEU	4109	19.17	17.63	19.85
DNK	480	15.87	11.31	17.43
ESP	4702	18.19	17.41	18.95
FIN	303	17.07	13.08	21.67
GBR	4316	17.02	15.26	18.08
GRC	499	18.47	16.81	22.06
HKG	852	19.55	17.88	21.86
HUN	720	17.73	15.52	19.68
IND	746	20.15	18.24	21.10
IRL	699	18.37	16.03	20.47
ITA	3725	19.61	17.07	21.81
JPN	885	19.71	15.96	22.17
KOR	628	14.17	12.25	15.70
LUX	1404	15.08	13.65	16.05
MAR	844	17.54	15.49	18.62
MEX	780	17.41	13.93	20.51
NLD	2744	16.93	14.77	18.21
POL	1562	17.41	15.38	18.73
PRT	1374	20.68	19.68	21.48
ROU	555	21.11	18.08	22.62
RUS	669	22.21	17.74	25.63
SGP	918	19.88	17.34	22.96
SWE	781	19.10	15.48	20.27
THA	379	16.67	11.60	17.58
TUN	447	12.79	9.56	15.23
TUR	740	19.74	17.36	20.37
USA	4104	17.07	15.58	18.07
ZAF	473	17.91	13.68	20.19
Total	55021	18.03	15.71	20.09

NOTE: Countries with at least 15 affiliates per year. Idiosyncratic Returns are based on the residuals from estimating Equation 3.

3 Impact of FDI Return Uncertainty on FDI Flows

This section investigates the effect of uncertainty on the direct investment activity of French MNFs.

3.1 Baseline Regressions

Our baseline regression specification is as follows:

$$\Delta COF_{a,t} = \alpha_1 X_{j,t} + \alpha_2 X_{s,t-1} + \alpha_3 X_{a,t-1} + \beta_1 \mathtt{DISP}_{j,t} + \gamma_a + \gamma_t \times \gamma_k + \varepsilon_{a,t} \tag{8}$$

where $\Delta COF_{a,t}$ is the log difference of the cumulative stock of the affiliate $a = \{s, j, k\}$ – owned by the parent firm s in the sector k of the country j – as of time t. As in Julio and Yook (2016) we use the log difference of the cumulative FDI position to avoid the issue of taking the logarithm of negative flows. All the regressions include country level controls $X_{j,t}$ for GDP growth, exchange rates changes, GDP per capita, trade openness and stock market return as in Julio and Yook (2016) – see the section A.1 for data construction. We also include a vector of lagged parent company controls $X_{s,t-1}$ to capture relevant firm characteristics for investment (e.g. Gilchrist and Himmelberg (1995) and Gala and Julio (2016)): the log of the total direct investment assets owned by the parent-firm to control for its size; the total number of foreign affiliates owned by the parent-firm to proxy alternative investment opportunities; and finally the parent-firm average return on investment to proxy the marginal return to capital. We add a vector of lagged affiliate characteristics $X_{a,t-1}$ to control for its financial constraint and investment opportunities: the size of the affiliate assets and its returns on investment. Finally, we follow Kovak et al. (2017) for the fixed effect structure: γ_a is an affiliate fixed effect that allows us to control for affiliates unobservable time-invariant characteristics, including its country and sector; $\gamma_t \times \gamma_k$ is a year by sector fixed effect that captures the business cycle of the sector.

The first column of Table 4 reports the estimation results of our baseline regression. The coefficient β_1 of our variable of interest $\mathtt{DISP}_{j,t}$ is negative, equal to -0.002, and significant at

Table 4: Idiosyncratic Uncertainty and FDI. Direct Effect and Effect Conditional on Parent Company Past Performance

	Δ COF$_{a,t}$			
	(1)	(2)	(3)	(4)
		Performance		
	Full Sample	Low	Medium	High
log GDP/cap.$_{j,t}$	0.089***	-0.092	0.275***	0.125***
	(0.028)	(0.078)	(0.056)	(0.024)
Δ GDP$_{j,t}$	0.229	0.504	-0.126	0.140
	(0.167)	(0.407)	(0.291)	(0.142)
Δ FX$_{j,t}$	-0.163***	-0.105	-0.149*	-0.241***
	(0.038)	(0.083)	(0.081)	(0.055)
Trade Openness$_{j,t}$($\%GDP$)	-0.000	-0.001**	0.000	0.000
	(0.000)	(0.000)	(0.001)	(0.000)
Stock Market Return$_{j,t}$	-0.000	0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
log Parent Assets$_{s,k,t-1}$	0.008	0.009	0.010	-0.006
	(0.006)	(0.013)	(0.013)	(0.010)
Parent Performance$_{s,k,t-1}$	0.001**	0.004*	0.008*	0.002**
	(0.001)	(0.002)	(0.004)	(0.001)
Nb. of Foreign Affiliates$_{s,k,t-1}$	-0.001	0.002	-0.000	-0.001
	(0.001)	(0.004)	(0.004)	(0.002)
log Affiliate Assets$_{a,t-1}$	-0.064***	-0.052***	-0.059***	-0.093***
	(0.007)	(0.017)	(0.011)	(0.010)
Affiliate Performance$_{a,t-1}$ (%)	0.001***	0.000	0.001**	0.001***
	(0.000)	(0.001)	(0.000)	(0.000)
$\mathtt{DISP}_{j,t}$	-0.002***	-0.004**	-0.002	-0.001
	(0.001)	(0.002)	(0.002)	(0.001)
Affiliate FE	Yes	Yes	Yes	Yes
Sector × Year FE	Yes	Yes	Yes	Yes
Observations	39499	10820	9266	17812
R^2	0.302	0.388	0.355	0.324
Effect in pcp. of an IQR shift:				
- $\mathtt{DISP}_{j,t}$	-0.904	-1.837	-1.026	-0.544
- Δ GDP$_{j,t}$	0.582	1.234	-0.336	0.364

NOTES: We report standard errors clustered at the country level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; a, s, k, j and t indexes affiliates, parent-firms, sectors, countries and years respectively.
We estimate the results above on a sample of 3056 French parent companies and their 10474 foreign affilates between 2001 and 2015 in 38 countries. See Section 2.3 for the construction of $\mathtt{DISP}_{j,t}$.
The last two lines present the contrasts of shifting from the 25^{th} percentile of the distribution of the selected variable to the 75^{th} while holding other variables constant at their mean value.

the one percent level. The sign of the coefficient is consistent with the literature on the adverse effects of uncertainty on investment. The magnitude of this estimated effect is substantial. Indeed, shifting from the 25th percentile of the distribution of uncertainty to the 75th percentile results in a 0.904 (s.e.= 0.412) points of percentage reduction in FDI growth rate – that is approximately one quarter of the average growth rate of FDI in our data, namely 3.37%. As a comparison, a similar shift in the distribution of GDP growth rate implies a 0.582 points of percentage increase in FDI growth rate.[10]

When it comes to the control variables, as expected an increase in the GDP growth rate of the destination country is associated with a higher flow of FDI to this country. The coefficient for Trade Openness is negative but not significantly different from zero at the 10% level. Depreciation of the local currency (that is a positive variation of the real FX rate) is associated with lower FDI. The sign and significance of the coefficients for parent company and affiliate characteristics provides an interesting complement to the results from Gala and Julio (2016): the negative coefficient of the size of the affiliate reflects the diminishing returns of investment opportunities rather than financial constraints. The positive but non statistically significant coefficient of the size of the parent company (after controlling for lagged returns) would indicate that financial constraints do not play a major role in the FDI of multinational firms. The coefficients of other control variables for parent company (returns on investment and number of affiliates) are not significantly different from zero.

We supplement our results with the Local Projection method of Jordà (2005)[11] to assess the persistence of the adverse effect of uncertainty on FDI. This is important with regards to the rebound effect associated with the wait and see mechanism highlighted by Bernanke (1983) and Bloom (2009). The initial negative effect should not be persistent and then turn positive, reflecting the wait and see pattern documented by Julio and Yook (2016). We estimate the

[10]We have also tested the effect of the lagged values of uncertainty, that is using $\mathtt{DISP}_{j,t-1}$ instead of $\mathtt{DISP}_{j,t}$ in our benchmark regressions. Lagged uncertainty shocks have no significant effects on cross-border investment. This is consistent with the fact that our measure of uncertainty exhibit a very low degree of persistence. It can also be related with Julio and Yook (2016) who show that the effect of uncertainty on FDI occurs mainly within the election years; years before elections are not associated with a fall in foreign investments.

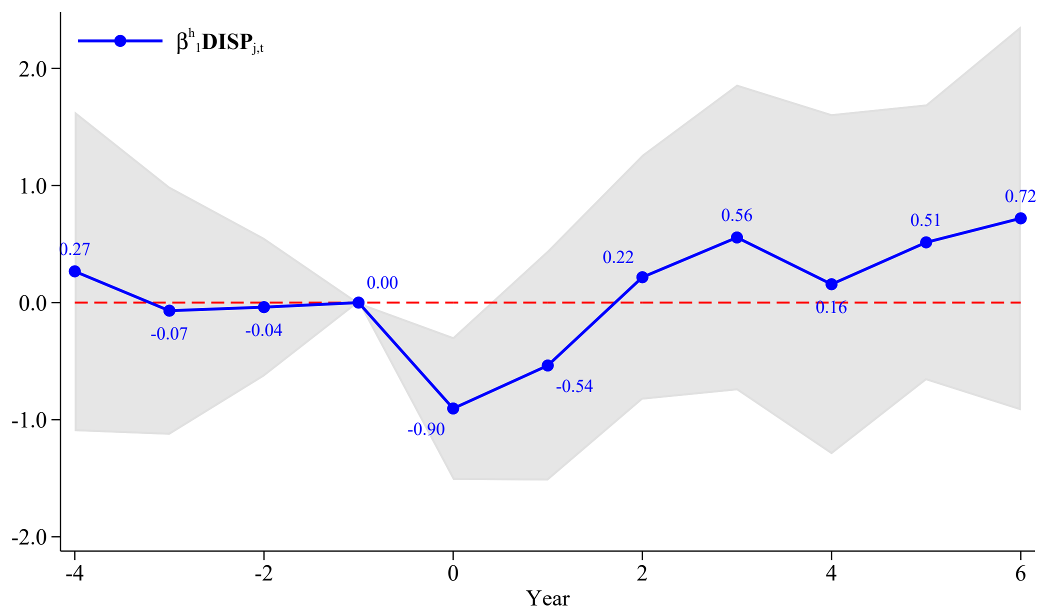
[11]See Crouzet et al. (2017) and Favara and Imbs (2015) for recent applications of Local Projection method to micro data.

following equation:

$$\Delta COF_{a,t+h} = \alpha_1^h X_{j,t} + \alpha_2^h X_{s,t-1} + \alpha_3^h X_{a,t-1} + \beta_1^h \mathtt{DISP}_{j,t} + \gamma_a^h + \gamma_t^h \times \gamma_k^h + \varepsilon_{a,t+h} \tag{9}$$

where h is the horizon of projection. Figure 2 shows the results. The sign of the coefficient remains negative for up to two years and turns positive until the end of the five year window, however it is not significantly different from zero at these horizons. Backward projections in Figure 2 show the absence of a pre-trend. There is no ex-ante effect depending on the intensity of the treatment.[12]

Figure 2: Affiliate Outcome Path Following an Interquartile Shift in the Distribution of Uncertainty



NOTE: This Figure presents estimates of β_1^h (scaled up by a 100 times an Interquartile Range shift of $\mathtt{DISP}_{j,t}$)) from estimating this equation for $h \in \{-4, 6\}$: $\Delta COF_{a,t+h} = \alpha_1^h X_{j,t} + \alpha_2^h X_{s,t-1} + \alpha_3^h X_{a,t-1} + \beta_1^h \mathtt{DISP}_{j,t} + \gamma_a^h + \gamma_t^h \times \gamma_k^h + \varepsilon_{a,t}$. 95% error bands are displayed in gray with standard errors clustered at the country level.

[12]The pre-trends also appear to be parallel for the various groups of size and performance. It will also be the case in 3 and A.4, see below.

3.2 The role of firm ex-ante performances

Insights from the trade and uncertainty literature suggest that firms react heterogeneously to increased volatility. To test whether the effect of uncertainty may be caused by a heterogeneous reactions across firm characteristics, we replicate our baseline regressions (8) and (9) for split samples, i.e. the sub-samples of firms grouped according to their ex-ante characteristics. Barrero et al. (2017) and Patnaik (2016) also use split-sample analyses to assess the effect of uncertainty according to the level of firm leverage and to the degree of competition, respectively.[13] We focus here on the role of firm ex-ante performances and estimate the following equation:

$$\begin{aligned}\Delta COF_{a,t+h} = &\sum_{g\in\Gamma}\left(\alpha^h_{1,g}X_{j,t} + \alpha^h_{2,g}X_{s,t-1} + \alpha^h_{3,g}X_{a,t-1} + \beta^h_{1,g}\mathtt{DISP}_{j,t}\right)\mathbf{1}_{\{a\in\Gamma^g_t\}} \\ &+ \gamma^h_a + \gamma^h_t \times \gamma^h_k + \varepsilon_{a,t+h}\end{aligned} \tag{10}$$

for $h \in \{-4, 6\}$ period ahead. Where Γ are firms groups based on their ex-ante performance defined as the average of the performance of its affiliate (see Equation 1)

$$\begin{cases} \Gamma_t^{(g=low)} & = \Gamma_t^{(P0,P40)} \\ \Gamma_t^{(g=medium)} & = \Gamma_t^{(P40,P60)} \\ \Gamma_t^{(g=high)} & = \Gamma_t^{(P60,P100)} \end{cases}$$

Columns (2)-(4) in Table 8 report the estimation results for $h = 0$ and Figure 3 presents the estimates of the coefficient β^h_1 of Equation (10) for various horizon h.

For most control variables, coefficients share the same sign and level of significance for the three groups of firms. When it comes to our main variable of interest, $\mathtt{DISP}_{j,t}$, the coefficient is significant only for firms with ex-ante low performances and substantially higher than estimated in average. Shifting from the 25th percentile of the distribution of uncertainty to the 75th

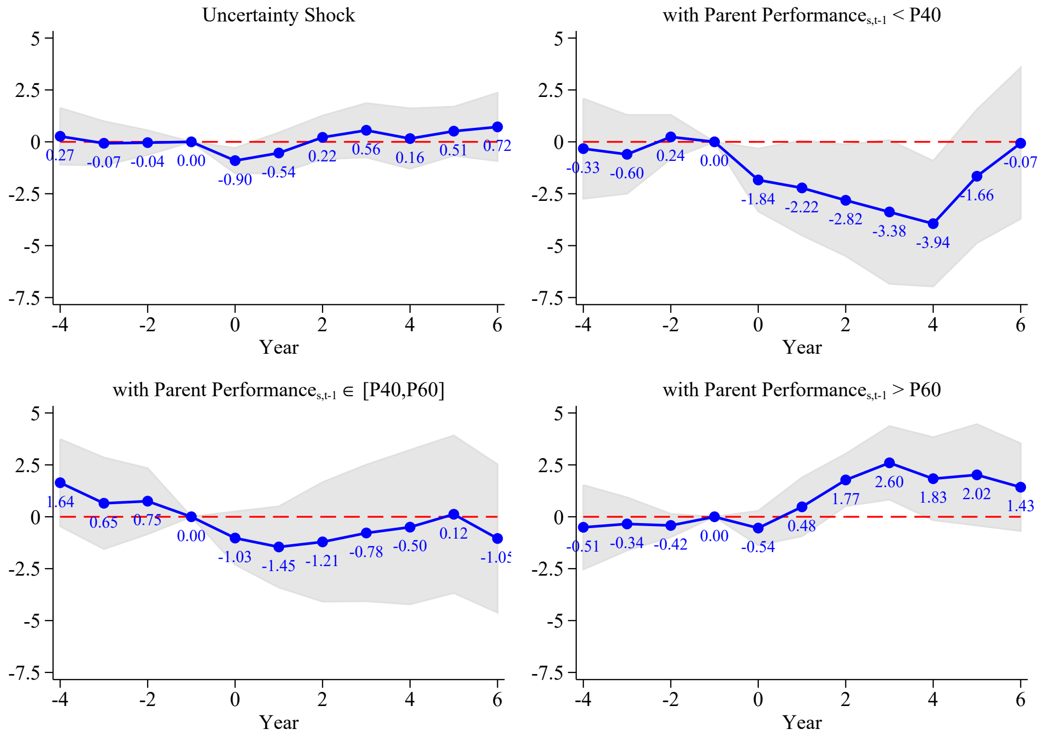
[13] See Zwick and Mahon (2017) for a split sample analysis of the effect of taxes on investment according to firm size.

percentile results in a reduction of FDI growth rate twice higher for these firms when compared with the full sample, e.g. a reduction of -3.38 of percentage points against -0.904.

Inspecting the dynamic responses in Figure 3 reveals a greater heterogeneity in the effects of uncertainty shocks on firms. The negative impact of return uncertainty for firms in the bottom 40% of the distribution becomes even more dramatic four years after the shock with a reduction of -3.94 percentage points in the FDI growth rate. Then, the impact becomes not significantly negative for higher horizons. The effect of uncertainty shocks turns out to be positive for the most performant firms (and significantly different from zero) two and three years after the shocks with a peak of 2.60 percentage points. These heterogeneous effects produce a huge gap of almost 6 points of percentage in FDI growth rate between most and less performing firms three years after the shocks.[14] Since we consider FDI growth rates, this transitory divergence between firms results in permanent divergence in the stock of assets held abroad. We find that most of the persistence is explained by the lack of recovery from the lower performing parent firms. Lastly, it is interesting to observe that the wait-and-see pattern observed for the entire sample of parent companies (e.g. the rebound effect) is actually driven by the heterogeneity of firm reactions to uncertainty.

[14]We also test the coefficient of the interaction of $\mathtt{DISP}_{j,t}$ and a dummy variable indicating that the firm belongs to the bottom 40 percent of past performance. We find that the slope of $\mathtt{DISP}_{j,t}$ for the low performance group is negative and statistically significant relative to the other group. The pattern of the response mostly matches that of our key result in Figure 3 (bottom and top right panel).

Figure 3: Affiliate Outcome Path Following an Interquartile Shift in the Distribution of Uncertainty Conditional on Parent Company Past Performance



NOTE: This Figure presents estimates of β_1^h (scaled up by a 100 times an Interquartile Range shift of $\texttt{DISP}_{j,t}$)) from estimating this equation for $h \in \{-4, 6\}$: $\Delta COF_{a,t+h} = \sum_{x\in\iota}(\alpha^h_{1,x} X_{j,t} + \alpha^h_{2,x} X_{s,t-1} + \alpha^h_{3,x} X_{a,t-1} + \beta^h_{1,x}\texttt{DISP}_{j,t})\mathbf{1}_{a\in\iota} + \gamma^h_a + \gamma^h_t \times \gamma^h_k + \varepsilon_{a,t}$. 95% error bands are displayed in gray with standard errors clustered at the country level. The left panel includes the entire sample, the center and right panel includes, respectively, only the affiliates of parent companies which were in the bottom 40% (respectively top 40%) of the performance distribution the year before.

4 Robustness

We attempt various comparison and validation exercises.

4.1 Asymmetric Uncertainty

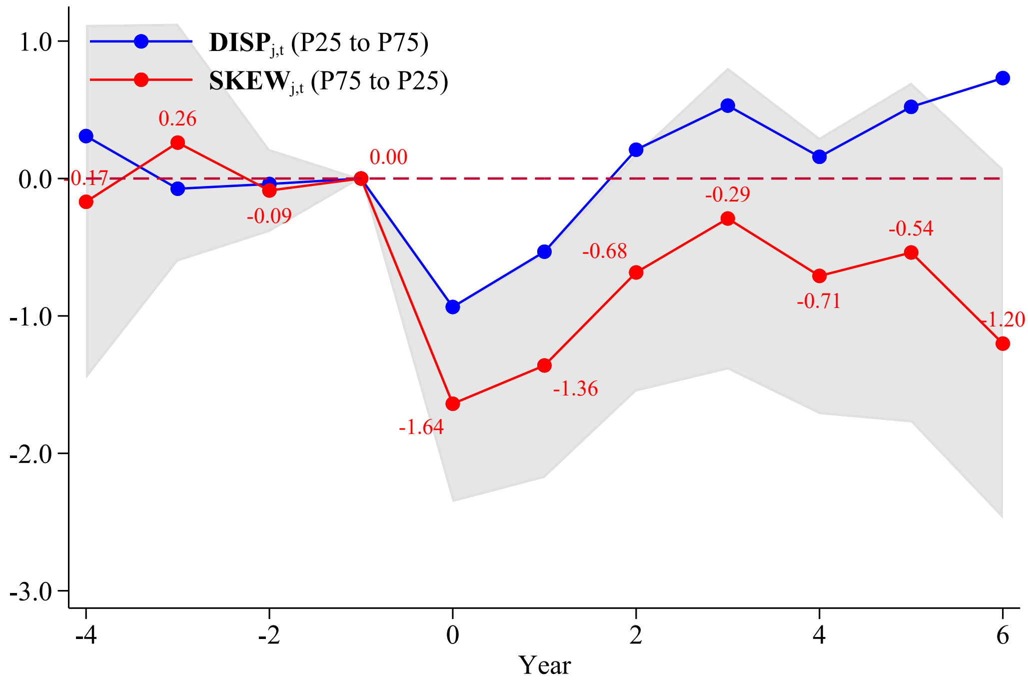
This section investigates the effects of asymmetric uncertainty. Our benchmark measure of uncertainty is based on the second order moment of the distribution of shocks to FDI returns. An increase in uncertainty is symmetric shift of the two sides of the distribution. We can generalize our methodology to consider asymmetric shifts of the distribution in two different ways.

First, we can consider higher moments of the distribution such as the skewness (the third order moment). The interest of the skewness is to consider asymmetric changes in risk, while our measure $\texttt{DISP}_{i,j}$ consists in symmetric changes for the two sides of the distribution. Indeed, a fall in the skewness corresponds to a relative increase in the probability of extremely bad realizations of shocks. By investigating the effects of skewness shocks on FDI, we contribute to the growing literature on the skewness dynamics in business and financial cycles (e.g. Ordonez, 2013; Orlik and Veldkamp, 2014; Bloom et al., 2016; Ruge-Murcia, 2017). Table 5 extends our baseline regression by including the $\texttt{SKEW}_{j,t}$ of the distribution as an explanatory variable. In column (1), we introduce both $\texttt{DISP}_{j,t}$ and $\texttt{SKEW}_{j,t}$ as explanatory variables while in column (2) only $\texttt{SKEW}_{j,t}$ is introduced. Our estimates of β_1 is robust to the inclusion of $\texttt{SKEW}_{j,t}$ as an additional control variables: the coefficient of $\texttt{DISP}_{j,t}$ (column 1 in Table 5) is slightly lower when compared to that of reported in column (1) of Table 4, but still highly significantly different from zero. Column (1) suggests that the magnitude of the impact of $\texttt{SKEW}_{j,t}$ on FDI is stronger than that of $\texttt{DISP}_{j,t}$. An interquartile range shift of the skewness generates a variation of 1.645 points of percentage of the FDI growth rate. It is twice higher than the effect of a similar shift of the dispersion, namely 0.844. This estimate of the impact of skewness shocks is roughly unchanged when we drop $\texttt{DISP}_{j,t}$ from the regression – see column (2) in Table 5. Figure 4 compares the dynamic effects of an decrease in $\texttt{SKEW}_{j,t}$ with that of an increase in $\texttt{DISP}_{j,t}$ depicted in 3. An interquartile range shift of the skewness generates a stronger and more persistent response of cross-border investments than a similar shift of the dispersion of shocks.

The second way to consider asymmetric change in uncertainty is to split the sample of $\texttt{DISP}_{j,t}$ into good and bad uncertainty as suggested by Bollerslev et al. (2017). We use the country-year mean of the residuals $u_{a,t}$ to make the distinction between good and bad uncertainty. Country-year dyads where the mean of the performance shocks is positive are assigned to the first group and country-year dyads with negative performance shocks on average are assigned to the second one.

Results are reported in columns (3)-(4) of the Table 5. The coefficient associated with $\texttt{DISP}_{j,t}$

Figure 4: Affiliate Outcome Path Following an Interquartile Shift in the Distribution of Skewness



NOTE: This Figure presents estimates of β_1^h (scaled up by a 100 times an Interquartile Range shift of $\mathtt{DISP}_{j,t}$) and β_2^h (scaled up by a 100 times an Interquartile Range shift of $\mathtt{SKEW}_{j,t}$) from estimating those equations for $h \in \{-4, 6\}$: $\Delta COF_{a,t+h} = \sum_{x\in\iota}(\alpha^h_{1,x} X_{j,t} + \alpha^h_{2,x} X_{s,t-1} + \alpha^h_{3,x} X_{a,t-1} + \beta^h_{1,x}\mathtt{DISP}_{j,t} + \gamma^h_a + \gamma^h_t \times \gamma^h_k + \varepsilon_{a,t}$. and $\Delta COF_{a,t+h} = \sum_{x\in\iota}(\alpha^h_{1,x} X_{j,t} + \alpha^h_{2,x} X_{s,t-1} + \alpha^h_{3,x} X_{a,t-1} + \beta^h_{2,x}\mathtt{SKEW}_{j,t} + \gamma^h_a + \gamma^h_t \times \gamma^h_k + \varepsilon_{a,t}$. 95% error bands are displayed in gray with standard errors clustered at the country level. The left panel includes the entire sample, the center and right panel includes, respectively, only the affiliates of parent companies which were in the bottom 40% (respectively top 40%) of the performance distribution the year before.

(column 3) is negative. Its order of magnitude is less than half that of an increase in $\mathtt{DISP}_{j,t}$ in the full sample and it is not significantly different from zero. Meanwhile in the sub-sample of countries with a positive mean, the effect is negative and much stronger. If we consider only bad uncertainty, the effect of an interquartile range shift (-1.436) is close to be twice higher than in our benchmark case (-0.904 in column 1 of Table 4).

Considering the skewness or the distinction between good and bad uncertainty highlights the asymmetric impact of uncertainty: rising dispersion on the left side of the distribution (low returns) is more painful than rising dispersion on the right side (high return). This conclusion is consistent with the model developed in Section B based on the role of financial frictions.

Lenders are exposed to default risk in the event of low FDI returns. In the event of high returns, this benefits the multinationals that receive the profits because the debt contract does not index the interest on the profits made. Lenders therefore react logically more strongly to an asymmetric increase in risk (biased towards low returns) than to a symmetric increase in risk, with a stronger increase in the risk premium at the origin of a fall in credit demand and cross-border investments by multinationals.

4.2 The role of firm size

This section investigates the role of firm size in shaping the effect of uncertainty on FDI. Size and performance are generally correlated (at least in theory, e.g. Melitz and Ottaviano (2008)) but that is not the case in our sample. Indeed, the coefficient of correlation between Parent Performance and Parent Size is around 0.06 (see Figure A.2). Therefore, we investigate how firm size influences the effect of uncertainty shocks. Results are reported in Figure A.4 replicate the Figure 3 using regressions (10) for deciles of ex-ante size instead of ex-ante performances. Large firms are not impacted by uncertainty shocks, whatever the horizons, while small firms are strongly and lastingly affected.

4.3 Alternative uncertainty proxies

This section shows the effects of uncertainty shocks on FDI using alternative proxies for uncertainty. Columns (1)-(4) of Table A.2 considers alternatively four alternative measure of uncertainty: the volatility of the local stock market, the country measure of Economic Policy Uncertainty, the Foreign Exchange rate return Volatility, and finally the average one-year ahead forecast errors of the IMF.

The estimated coefficient is significantly different from zero only for foreign exchange rate volatility. As explained by Jeanneret (2016) the sign of the relation between FX volatility and FDI is actually both theoretically and empirically ambiguous. Interestingly, inspecting the dynamic effects of FX uncertainty confirms the importance of firm heterogeneity. Figure

Table 5: Asymmetric Uncertainty and FDI.

	Δ COF$_{a,t}$			
	(1)	(2)	(3)	(4)
	Full Sample		$\texttt{MEAN}_{j,t}$	
			≥ 0	≤ 0
log GDP/cap.$_{j,t}$	0.088***	0.082***	0.022	0.112***
	(0.028)	(0.028)	(0.052)	(0.035)
Δ GDP$_{j,t}$	0.267	0.300*	0.533*	0.120
	(0.160)	(0.159)	(0.291)	(0.196)
Δ FX$_{j,t}$	-0.162***	-0.150***	-0.159*	-0.114**
	(0.041)	(0.040)	(0.081)	(0.045)
Trade Openness$_{j,t}$(%GDP)	-0.000	-0.000	-0.000	-0.000*
	(0.000)	(0.000)	(0.001)	(0.000)
Stock Market Return$_{j,t}$	-0.000	-0.000	0.000	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
log Parent Assets$_{s,k,t-1}$	0.008	0.007	0.001	0.010
	(0.006)	(0.006)	(0.009)	(0.010)
Parent Performance$_{s,k,t-1}$	0.001**	0.001**	0.002**	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Nb. of Foreign Affiliates$_{s,k,t-1}$	-0.001	-0.001	-0.001	-0.002
	(0.001)	(0.001)	(0.002)	(0.002)
log Affiliate Assets$_{a,t-1}$	-0.063***	-0.063***	-0.054***	-0.069***
	(0.007)	(0.007)	(0.007)	(0.011)
Affiliate Performance$_{a,t-1}$ (%)	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
$\texttt{DISP}_{j,t}$	-0.002***		-0.001	-0.004***
	(0.001)		(0.001)	(0.001)
$\texttt{SKEW}_{j,t}$	0.014***	0.014***		
	(0.003)	(0.003)		
Affiliate FE	Yes	Yes	Yes	Yes
Sector × Year FE	Yes	Yes	Yes	Yes
Observations	39499	39499	17120	19055
R^2	0.303	0.303	0.391	0.391
Effect in pcp. of an IQR shift:				
- $\texttt{DISP}_{j,t}$	-0.844		-0.460	-1.436
- $\texttt{SKEW}_{j,t}$	1.645	1.672		

NOTES: We report standard errors clustered at the country level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; a, s, k, j and t indexes affiliates, parent-firms, sectors, countries and years respectively.
We estimate the results above on a sample of 3056 French parent companies and their 10474 foreign affiliates between 2001 and 2015 in 38 countries. See Section 2.3 for the construction of $\texttt{DISP}_{j,t}$.
The last two lines present the contrasts of shifting from the 25^{th} percentile of the distribution of the selected variable to the 75^{th} while holding other variables constant at their mean value.

A.5 replicates the Figure 3 using regressions (10) with FX volatility instead of $\texttt{DISP}_{j,t}$. As in our benchmark, high performing firms react positively to an increase in uncertainty while low performing firms experience an important and lastingly reduction in FDI.

Our results for stock price volatility are consistent with Gourio et al. (2016) who report significant effects of uncertainty on total capital inflows who turn out to be non significant when they consider only FDI inflows.[15] We conclude that using micro-data allows us to build a firm-level based measure of uncertainty which may be more relevant than aggregate measures to capture its effects on firms decision.

4.4 Placebo Inference

In the baseline specification, we clustered standard errors at the country level. This provided us with standard errors that are asymptotically robust to serial auto-correlation in the error term. Here we implement Chetty et al. (2009)'s non-parametric permutation test[16] of $\beta_1^h = 0$.

To do so, we randomly reassign the uncertainty time serie across firms and then we re-estimate the baseline regression. We repeat this process 2000 times in order to obtain an empirical distribution of the placebo coefficients $\hat{\beta}_1^{h,p}$. If $\texttt{DISP}_{j,t}$ had no effect on FDI, we would expect our baseline estimate to fall somewhere in the middle of the distribution of the coefficients of the placebo coefficients $\hat{\beta}_1^{h,p}$. Since that test does not rely on any parametric assumption regarding the structure of the error term, it is immune to the over-rejection of the null hypothesis highlighted by Bertrand et al. (2004).

We plot the distribution of the placebo coefficients in Figure A.6. The figure confirms that our coefficients of interest $\beta_1^{h=0}$ (the blue connected markers) lie outside of the [p0.5,p99.5] interval (the light blue lines) of the distribution of placebo coefficients. Meanwhile, the estimates of $\beta_1^{h<0}$ fall within the bounds of the distribution of placebos. This exercise confirms that uncertainty has a negative effect on firm growth.

We repeat the same exercise for the other key finding of this paper. We randomly permute

[15] See the column 3 in Table 21 of Gourio et al. (2016)

[16] See Malgouyres et al. (2019) for a more recent application

$\mathtt{DISP}_{j,t}$ within the sub-samples of low and high parent company ex-ante performance. Figure A.7 confirms that each estimate of $\beta^{h>0}_{1,g=low}$ lies outside of its $[0.5, 99.5]$ interval of its placebos (the blue lines). Whereas the estimates of $\beta^{h>0}_{1,g=high}$ only fall outside of their intervals (in red) for $h = 3$. Although this estimates are fairly close to the outside of the distribution of the placebos for $h = \{1, 2, 4, 5\}$.

4.5 Specification Sensitivity

We show that the coefficient produced by our specification is not an outlier. We follow a procedure somewhat similar to that of Campbell et al. (2019). We omit 1-by-1 each control variable and plot the results in purple in Figure A.9. Then we test the following list of fixed effects: $s{\times}m{\times}jt$; $sm{\times}jt$; $sm{\times}t$; $s{\times}m{\times}j$; $m{\times}jt$; $sjm{\times}t$; $sm{\times}jm{\times}t$; t.. All specifications include the two following vectors of controls: $X_{j,t}$ = {GDP per capita, GDP growth, Exchange Rate growth, Trade Openness, Market Return}; $X_{s,t-1}$ = {Size, Performance, Number of Affiliates}. We plot the results in gold in Figure A.9. Our baseline specification falls in the middle of the distribution of the coefficients. There is one outlying result for the specification that does not include any time fixed-effect. Including the contemporaneous level of skewness and/or the lagged value of uncertainty does not change our estimates.

4.6 Sample Sensitivity

Since our sample includes events such as the Great Financial Crisis (2008 and 2009), we wish to check whether our results are robust to the omission of any particular year. We run the same baseline regressions while omitting turn by turn any year between 2001 and 2015. Results are quantitatively and qualitatively the same using these specifications as on the full sample; see the thin blue lines in Figure A.8. It shows that our specification satisfyingly accounts for the complex dynamics of our sample period. This estimate is also statistically highly significant and robust to taking out any of our clusters at the sector (red lines) and country level (green lines).

4.7 1st Stage Specification

We now present the results from estimating out baseline specification but using the dispersion of residuals generated by different specifications of the first stage. It also include a specification of $\texttt{DISP}_{j,t}$ that excludes the affiliate from the computation of the standard deviation and a specification in which we replace the standard deviation with the interquartile range. Figure A.10 shows that the estimation with the baseline 1st stage is not an outlier. The one outlying specification that exhibits the highest contemporaneous loss and the highest over-compensation is the one that includes both an affiliate fixed effect and a firm×year fixed effect. Although this specification allows us to isolate a truly idiosyncratic shock to the affiliate performance, it restrict the sample to multi-affiliate firms which constitutes about 75% of the sample. It gives rise to a sample selection issue. At the other end of the spectrum, the specification with the lowest fall in contemporaneous investment only includes a destination×sector fixed effect as well as an AR(1) term.

5 Conclusion

The main motivation of this study was to extract the information regarding uncertainty that is embedded in FDI assets held abroad by french residents. We build a novel country and time-varying proxy for uncertainty based on the idiosyncratic volatility of the returns of French Foreign Direct Investment assets. Given this measure of uncertainty, we estimate how FDI react to uncertainty by regressing the individual FDI outflows by French MNF on our measure of uncertainty together with a set of relevant control variables and fixed effects.

An innovation in micro-uncertainty has a direct negative short-term impact on firm-level flows to the affected country whereas commonly used proxy for risk/uncertainty fail to explain most or any variation in flows. Following a one interquartile range increase in uncertainty in one country, French MNF decrease the rate of their direct investments to the affected country by as much as 0.904 (s.e.= 0.412) points of percentage. This effect decreases with the performance of the parent firm. Using Local Projections, we show that on average, it has little persistence beyond the initial shock. However, this effect hides strong parent-firm level heterogeneity. Indeed, parent companies with low ex-ante performance never recover while, higher performing parent companies over compensate in the following periods.

Our empirical results suggest a cleansing effect of uncertainty shocks. The literature on cleansing effect demonstrated that during recesssions less productive firms exit from the market while the most productive survive (Caballero and Hammour, 1994; Foster et al., 2016; Osotimehin and Pappadà, 2016; Aghion et al., 2019). We do not directly measure productivity of firms in our database, but if we proxy it by the return of FDI, our results suggest a cleansing effect too. Indeed, several years after an increase of uncertainty in a country, we should expect a higher level of assets held by ex-ante high performing firms and a lower level of assets held by ex-ante low performing firms. Interestingly, this reallocation process appears more important between low and high performing firms than between small and large firms. Further researches should be devoted to understand the mechanisms behind the heterogeneous behavior of firms and the potential role of irreversibilities and financial constraints.

References

Aghion, P., A. Bergeaud, G. Cette, R. Lecat, and H. Maghin (2019). Coase Lecture-the Inverted-U Relationship between Credit Access and Productivity Growth. Economica 86(341), 1–31.

Aizenman, J. and N. Marion (2004). The merits of horizontal versus vertical FDI in the presence of uncertainty. Journal of International economics 62(1), 125–148.

Anderson, E. W., E. Ghysels, and J. L. Juergens (2009). The impact of risk and uncertainty on expected returns. Journal of Financial Economics 94(2), 233–263.

Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang (2006). The cross-section of volatility and expected returns. The Journal of Finance 61(1), 259–299.

Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang (2009). High idiosyncratic volatility and low returns: International and further US evidence. Journal of Financial Economics 91(1), 1–23.

Atanassov, J., B. Julio, and T. Leng (2018). The bright side of political uncertainty: The case of R&D.

Baker, S. R., N. Bloom, and S. J. Davis (2016). Measuring economic policy uncertainty. The Quarterly Journal of Economics 131(4), 1593–1636.

Bar-Ilan, A. and W. C. Strange (1996). Investment lags. The American Economic Review 86(3), 610–622.

Barrero, J. M., N. Bloom, and I. Wright (2017). Short and long run uncertainty. Technical report, National Bureau of Economic Research.

Bernanke, B. S. (1983). Irreversibility, uncertainty, and cyclical investment. The Quarterly Journal of Economics 98(1), 85–106.

Bernanke, B. S., M. Gertler, and S. Gilchrist (1999). The financial accelerator in a quantitative business cycle framework. In J. B. Taylor and M. Woodford (Eds.), Handbook of Macroeconomics, Volume 1 of Handbook of Macroeconomics, Chapter 21, pp. 1341–1393. Elsevier.

Bertrand, M., E. Duflo, and S. Mullainathan (2004). How much should we trust differences-in-differences estimates? The Quarterly journal of economics 119(1), 249–275.

Blanchard, O. and J. Acalin (2016). PB 16-17 What Does Measured FDI Actually Measure?

Bloom, N. (2009). The impact of uncertainty shocks. econometrica 77(3), 623–685.

Bloom, N. (2014). Fluctuations in uncertainty. The Journal of Economic Perspectives 28(2), 153–175.

Bloom, N., M. Floetotto, N. Jaimovich, I. Saporta-Eksten, and S. J. Terry (2018). Really uncertain business cycles. Econometrica 86(3), 1031–1065.

Bloom, N., F. Guvenen, S. Salgado, et al. (2016). Skewed business cycles. In 2016 Meeting Papers, Number 1621. Society for Economic Dynamics.

Bollerslev, T., S. Z. Li, and B. Zhao (2017). Good volatility, bad volatility, and the cross section of stock returns. Journal of Financial and Quantitative Analysis, 1–57.

Boutchkova, M., H. Doshi, A. Durnev, and A. Molchanov (2012). Precarious politics and return volatility. Review of Financial Studies 25(4), 1111–1154.

Caballero, R. J. and M. L. Hammour (1994). The cleansing effect of recessions. The American Economic Review, 1350–1368.

Campbell, D., K. Mau, et al. (2019). Trade Induced Technological Change: Did Chinese Competition Increase Innovation in Europe? Technical report.

Chetty, R., A. Looney, and K. Kroft (2009). Salience and taxation: Theory and evidence. American economic review 99(4), 1145–77.

Christiano, L. J., R. Motto, and M. Rostagno (2014, January). Risk Shocks. American Economic Review 104(1), 27–65.

Crouzet, N., N. R. Mehrotra, et al. (2017). Small and Large Firms Over the Business Cycle. Technical report.

Cushman, D. (1985). Real Exchange Rate Risk, Expectations, and the Level of Direct Investment. The Review of Economics and Statistics 67(2), 297–308.

Dang, T. L., F. Moshirian, and B. Zhang (2015). Commonality in news around the world. Journal of Financial Economics 116(1), 82–110.

De Sousa, J., A.-C. Disdier, and C. Gaigné (2018). Export decision under risk.

Dixit, A. (1992). Investment and hysteresis. The Journal of Economic Perspectives 6(1), 107–132.

Favara, G. and J. Imbs (2015). Credit supply and the price of housing. American Economic Review 105(3), 958–92.

Fernández-Arias, E. and R. Hausmann (2001). Foreign direct investment: Good cholesterol? Inter-American Development Bank, Research Department Working Paper No 417.

Fillat, J. L. and S. Garetto (2015). Risk, returns, and multinational production. The Quarterly Journal of Economics 130(4), 2027–2073.

Foster, L., C. Grim, and J. Haltiwanger (2016). Reallocation in the Great Recession: cleansing or not? Journal of Labor Economics 34(S1), S293–S331.

Gala, V. and B. Julio (2016). Firm Size and Corporate Investment.

Ghosal, V. and P. Loungani (2000). The differential impact of uncertainty on investment in small and large businesses. Review of Economics and Statistics 82(2), 338–343.

Gilchrist, S. and C. P. Himmelberg (1995). Evidence on the role of cash flow for investment. Journal of Monetary Economics 36(3), 541–572.

Goldberg, L. and C. Kolstad (1995). Foreign Direct Investment, Exchange Rate Variability and Demand Uncertainty. International Economic Review 36(4), 855–73.

Gourio, F., M. Siemer, and A. Verdelhan (2016). Uncertainty and International Capital Flows.

Guiso, L. and G. Parigi (1999). Investment and demand uncertainty. The Quarterly Journal of Economics 114(1), 185–227.

Handley, K. and N. Limao (2015). Trade and investment under policy uncertainty: theory and firm evidence. American Economic Journal: Economic Policy 7(4), 189–222.

Handley, K. and N. Limão (2017). Policy uncertainty, trade, and welfare: Theory and evidence for china and the united states. American Economic Review 107(9), 2731–83.

Helpman, E., M. J. Melitz, and S. R. Yeaple (2004). Export versus fdi with heterogeneous firms. American economic review 94(1), 300–316.

Héricourt, J. and C. Nedoncelle (2018). Multi-destination firms and the impact of exchange-rate risk on trade. Journal of Comparative Economics.

Jeanneret, A. (2016, Aug). International Firm Investment under Exchange Rate Uncertainty. Rev. Financ. 20(5), 2015–2048.

Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. American Economic Review 95(1), 161–182.

Julio, B. and Y. Yook (2016). Policy uncertainty, irreversibility, and cross-border flows of capital. Journal of International Economics 103, 13–26.

Jurado, K., S. C. Ludvigson, and S. Ng (2015). Measuring uncertainty. The American Economic Review 105(3), 1177–1216.

Kovak, B. K., L. Oldenski, and N. Sly (2017). The labor market effects of offshoring by us multinational firms: Evidence from changes in global tax policies. Technical report, National Bureau of Economic Research.

Lewis, L. T. (2014). Exports versus multinational production under nominal uncertainty. Journal of International Economics 94(2), 371–386.

Malgouyres, C., T. Mayer, and C. Mazet-Sonilhac (2019). Technology-induced Trade Shocks? Evidence from Broadband Expansion in France. CEPR Discussion Papers 13847, C.E.P.R. Discussion Papers.

Marmer, V. and M. E. Slade (2018). Investment and uncertainty with time to build: Evidence from entry into us copper mining. Journal of Economic Dynamics and Control 95, 233–254.

Melitz, M. J. and G. I. Ottaviano (2008). Market size, trade, and productivity. The review of economic studies 75(1), 295–316.

Mohn, K. and B. Misund (2009). Investment and uncertainty in the international oil and gas industry. Energy Economics 31(2), 240–248.

Morck, R., B. Yeung, and W. Yu (2000). The information content of stock markets: why do emerging markets have synchronous stock price movements? Journal of Financial Economics 58(1), 215 – 260. Special Issue on International Corporate Governance.

Ordonez, G. (2013). The asymmetric effects of financial frictions. Journal of Political Economy 121(5), 844–895.

Orlik, A. and L. Veldkamp (2014). Understanding uncertainty shocks and the role of black swans. Technical report, National Bureau of Economic Research.

Osotimehin, S. and F. Pappadà (2016). Credit frictions and the cleansing effect of recessions. The Economic Journal 127(602), 1153–1187.

Patnaik, R. (2016). Competition and the real effects of uncertainty.

Pindyck, R. S. (1991). Irreversibility, uncertainty, and investment. Journal of Economic Literature 29(3), 1110–1148.

Ramondo, N., V. Rappoport, and K. J. Ruhl (2013). The proximity-concentration tradeoff under uncertainty. Review of Economic Studies 80(4), 1582–1621.

Rodrik, D. (1991). Policy uncertainty and private investment in developing countries. Journal of Development Economics 36(2), 229–242.

Ruge-Murcia, F. (2017). Skewness risk and bond prices. Journal of Applied Econometrics 32(2), 379–400.

Russ, K. N. (2012). Exchange rate volatility and first-time entry by multinational firms. Review of World Economics 148(2), 269–295.

Stein, L. C. and E. Stone (2013). The effect of uncertainty on investment, hiring, and r&d: Causal evidence from equity options.

Townsend, R. M. (1979). Optimal contracts and competitive markets with costly state verification. Journal of Economic Theory 21(2), 265–293.

Vicard, V. (2018). The exorbitant privilege of high tax countries. Working paper.

Zwick, E. and J. Mahon (2017, January). Tax policy and heterogeneous investment behavior. American Economic Review 107(1), 217–48.

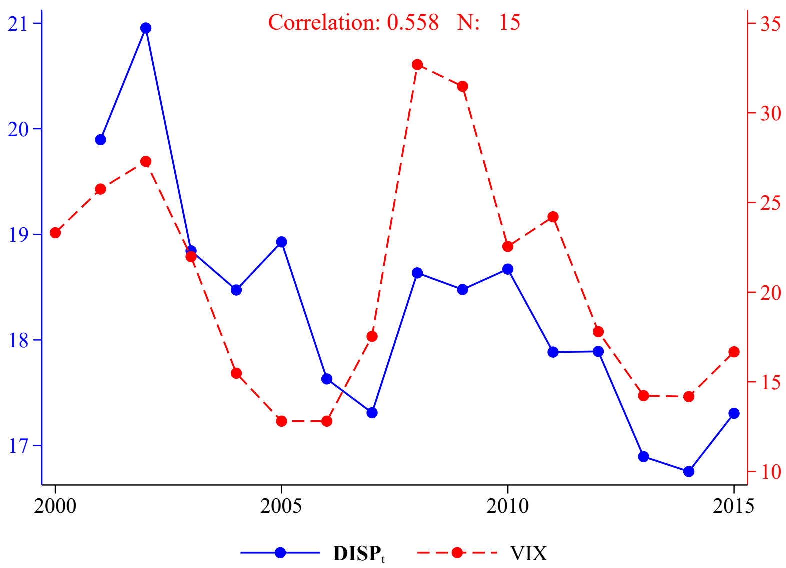
A Appendix

A.1 Data

Stock Price Volatility (SPV), GDP and GDP per capita are from the World Development Indicators (WDI) database from the World Bank. We obtain daily exchange rates against the Euro from World Market Reuters to calculate their growth rate by taking the log difference and then compute yearly average and volatility measures. The VIX is the implied volatility index computed by the CBOE and EPU is the Economic Policy Uncertainty Index from Baker et al. (2016). ΔGDP is computed by taking the log difference between year t and year $t-1$. Macro forecast errors are the dispersion of the IMF 1 year ahead forecast errors of GDP growth, inflation and current account balance.

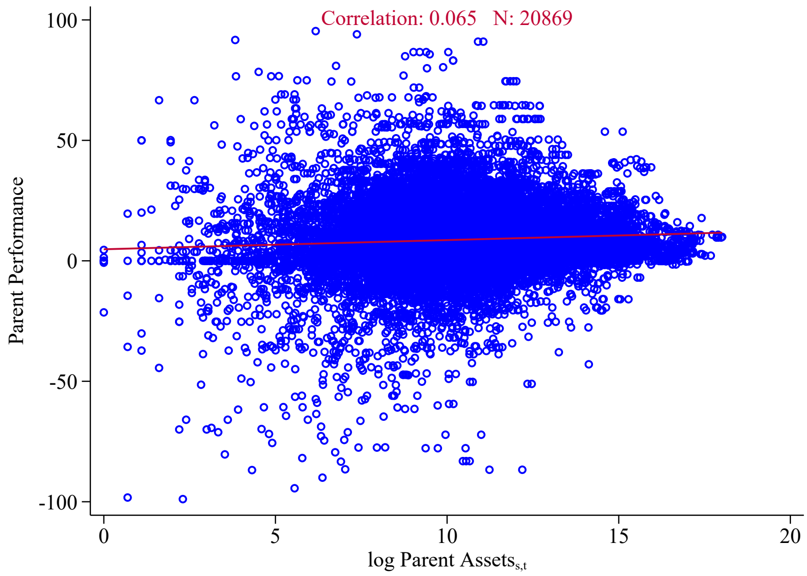
A.2 Additional Figures and Tables

Figure A.1: FDI Return Uncertainty and the VIX



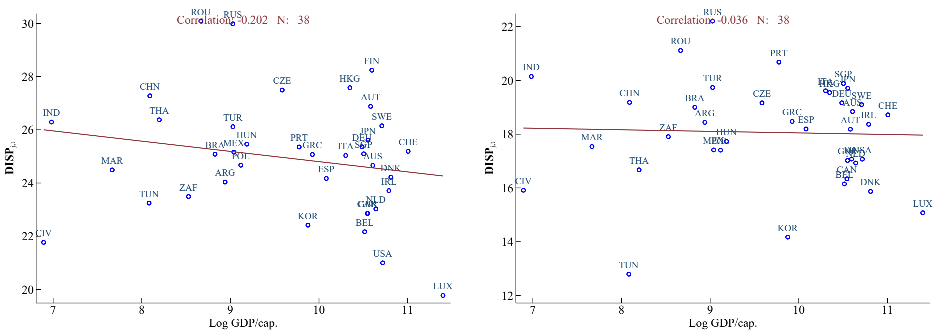
NOTE: Banque de France data and authors' computations.

Figure A.2: Size and Performance



NOTE: Banque de France data and authors' computations. The performance of the parent company is defined as the average performance of its affiliate. Size is the sum of assets held abroad by the parent company.

Figure A.3: Uncertainty and GDP/cap.



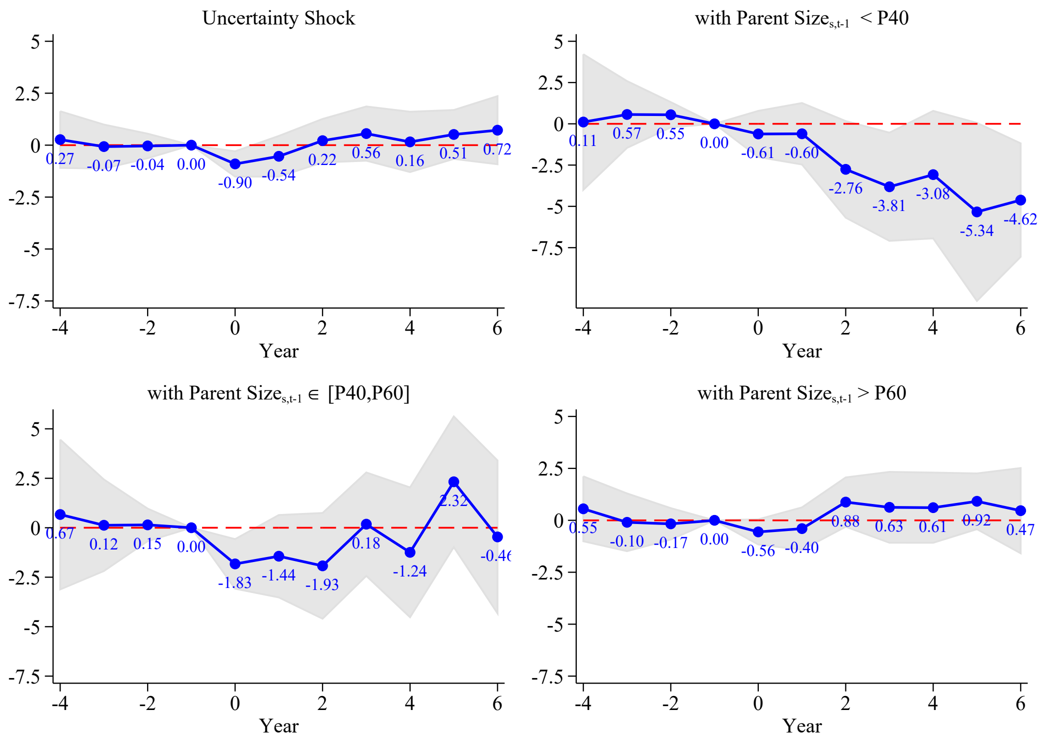
NOTE: Banque de France data and authors' computations.

Table A.1: Idiosyncratic Uncertainty and FDI. Baseline and Parent Company Characteristics

	Δ COF$_{a,t}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Performance			Size	
	Full Sample	Low	Medium	High	Small	Medium	Big
log GDP/cap.$_{j,t}$	0.089***	-0.092	0.275***	0.125***	0.002	0.230***	0.132***
	(0.028)	(0.078)	(0.056)	(0.024)	(0.082)	(0.080)	(0.035)
Δ GDP$_{j,t}$	0.229	0.504	-0.126	0.140	0.371	-0.451	0.246
	(0.167)	(0.407)	(0.291)	(0.142)	(0.499)	(0.276)	(0.185)
Δ FX$_{j,t}$	-0.163***	-0.105	-0.149*	-0.241***	-0.006	-0.232**	-0.179***
	(0.038)	(0.083)	(0.081)	(0.055)	(0.098)	(0.089)	(0.058)
Trade Openness$_{j,t}$(*%GDP*)	-0.000	-0.001**	0.000	0.000	0.000	0.001*	-0.000
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Stock Market Return$_{j,t}$	-0.000	0.000	-0.000	0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
log Parent Assets$_{s,k,t-1}$	0.008	0.009	0.010	-0.006	0.022	-0.011	-0.008
	(0.006)	(0.013)	(0.013)	(0.010)	(0.014)	(0.030)	(0.008)
Parent Performance$_{s,k,t-1}$	0.001**	0.004*	0.008*	0.002**	0.001	0.001	0.000
	(0.001)	(0.002)	(0.004)	(0.001)	(0.001)	(0.002)	(0.001)
Nb. of Foreign Affiliates$_{s,k,t-1}$	-0.001	0.002	-0.000	-0.001	-0.006	0.002	0.002
	(0.001)	(0.004)	(0.004)	(0.002)	(0.009)	(0.003)	(0.001)
log Affiliate Assets$_{a,t-1}$	-0.064***	-0.052***	-0.059***	-0.093***	-0.048***	-0.036***	-0.075***
	(0.007)	(0.017)	(0.011)	(0.010)	(0.010)	(0.012)	(0.008)
Affiliate Performance$_{a,t-1}$ (%)	0.001***	0.000	0.001**	0.001***	-0.000	0.000	0.001**
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
DISP$_{j,t}$	-0.002***	-0.004**	-0.002	-0.001	-0.001	-0.005***	-0.001*
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Affiliate FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	39499	10820	9266	17812	6300	5554	26115
R^2	0.302	0.388	0.355	0.324	0.457	0.470	0.303
Effect in pcp. of an IQR shift:							
- DISP$_{j,t}$	-0.904	-1.837	-1.026	-0.544	-0.615	-1.829	-0.557
- Δ GDP$_{j,t}$	0.582	1.234	-0.336	0.364	0.900	-1.097	0.645

NOTES: We report standard errors clustered at the country level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; a, s, k, j and t indexes affiliates, parent-firms, sectors, countries and years respectively. We estimate the results above on a sample of 3056 French parent companies and their 10474 foreign affilates between 2001 and 2015 in 38 countries. See Section 2.3 for the construction of DISP$_{j,t}$.
The last two lines present the contrasts of shifting from the 25th percentile of the distribution of the selected variable to the 75th while holding other variables constant.

Figure A.4: Affiliate Outcome Path Following an Interquartile Shift in the Distribution of Uncertainty Conditional on Parent Company Past Size



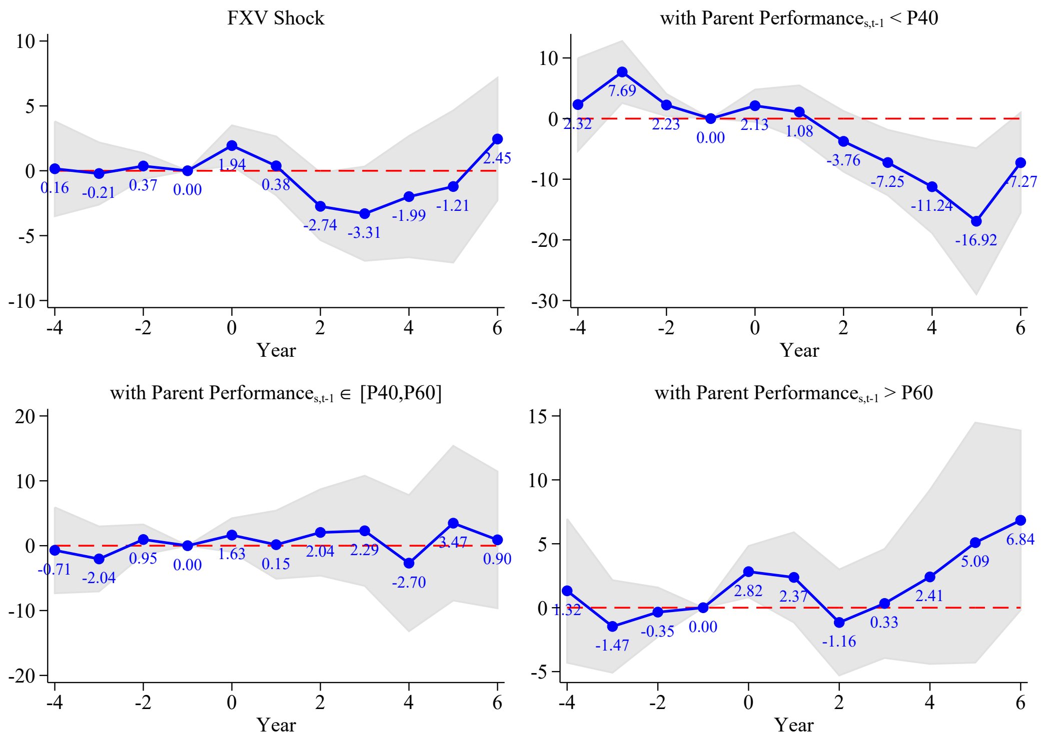
NOTE: This Figure presents estimates of β_1^h (scaled up by a 100 times an Interquartile Range shift of $\mathtt{DISP}_{j,t}$)) from estimating this equation for $h \in \{-4, 6\}$: $\Delta COF_{a,t+h} = \sum_{x \in \iota}(\alpha_{1,x}^h X_{j,t} + \alpha_{2,x}^h X_{s,t-1} + \alpha_{3,x}^h X_{a,t-1} + \beta_{1,x}^h \mathtt{DISP}_{j,t})\mathbf{1}_{a \in \iota} + \gamma_a^h + \gamma_t^h \times \gamma_k^h + \varepsilon_{a,t}$. 95% error bands are displayed in gray with standard errors clustered at the country level. The left panel includes the entire sample, the center and right panel includes, respectively, only the affiliates of parent companies which were in the bottom 40% (respectively top 40%) of the performance distribution the year before.

Table A.2: Standard Risk Proxy and FDI

	Δ COF$_{a,t}$			
	(1)	(2)	(3)	(4)
log GDP/cap.$_{j,t}$	0.158***	0.060*	0.124***	0.151***
	(0.037)	(0.033)	(0.033)	(0.034)
Δ GDP$_{j,t}$	0.518**	0.595**	0.480**	0.470*
	(0.233)	(0.263)	(0.191)	(0.253)
Δ FX$_{j,t}$	-0.151***	-0.136**	-0.150***	-0.157***
	(0.050)	(0.056)	(0.043)	(0.048)
Trade Openness$_{j,t}$$(\%GDP)$	-0.000	-0.001	-0.000	-0.000
	(0.000)	(0.001)	(0.000)	(0.000)
Stock Market Return$_{j,t}$	0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
log Parent Assets$_{s,k,t-1}$	0.016**	0.026***	0.016**	0.016**
	(0.008)	(0.006)	(0.007)	(0.008)
Parent Performance$_{s,k,t-1}$	0.002***	0.001**	0.002***	0.002***
	(0.001)	(0.001)	(0.000)	(0.001)
Nb. of Foreign Affiliates$_{s,k,t-1}$	0.000	-0.001	-0.000	0.000
	(0.002)	(0.002)	(0.001)	(0.002)
log Affiliate Assets$_{a,t-1}$	-0.102***	-0.101***	-0.100***	-0.102***
	(0.010)	(0.013)	(0.009)	(0.010)
Affiliate Performance$_{a,t-1}$ (%)	-0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Stock Price Volatility$_{j,t}$	0.001			
	(0.001)			
Econ. Policy Unc.$_{j,t}$		0.000		
		(0.000)		
Foreign Exchange Volatility$_{j,t}$			0.790**	
			(0.324)	
Macro FC ERR$_{j,t}$				0.000
				(0.002)
Affiliate FE	Yes	Yes	Yes	Yes
Sector × Year FE	Yes	Yes	Yes	Yes
Observations	36787	24618	40537	36804
R^2	0.299	0.304	0.290	0.299
Effect in pcp. of an IQR shift:				
- Variable of Interest	0.619	0.560	1.941	0.000789
- Δ GDP$_{j,t}$	1.389	1.449	1.244	1.264

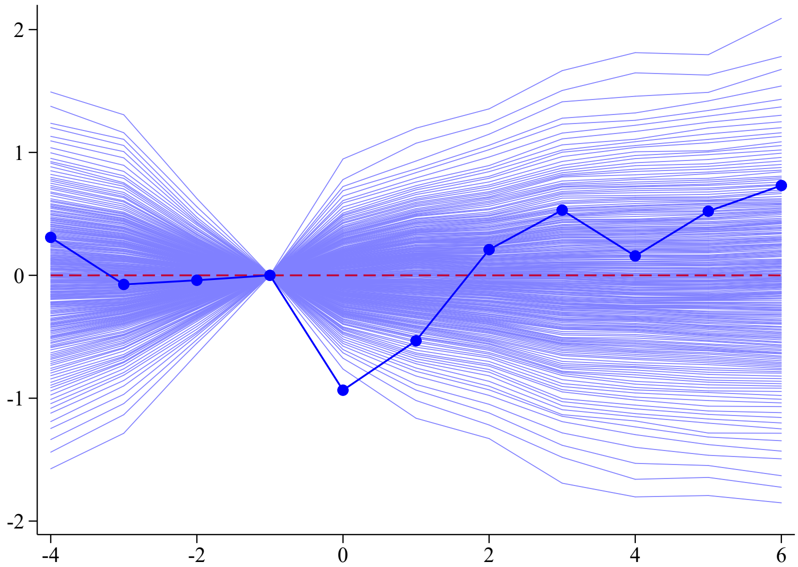
NOTES: We report standard errors clustered at the country level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; a, s, k, j and t indexes affiliates, parent-firms, sectors, countries and years respectively.
We estimate the results above on a sample of 3056 French parent companies and their 10474 foreign affilates between 2001 and 2015 in 38 countries. See Section 2.3 for the construction of $\mathtt{DISP}_{j,t}$.
The last two lines present the contrasts of shifting from the 25^{th} percentile of the distribution of the selected variable to the 75^{th} while holding other variables constant.

Figure A.5: Affiliate Outcome Path Following an Interquartile Shift in the Distribution of Foreign Exchange Rate Volatility Conditional on Parent Company Past Performance



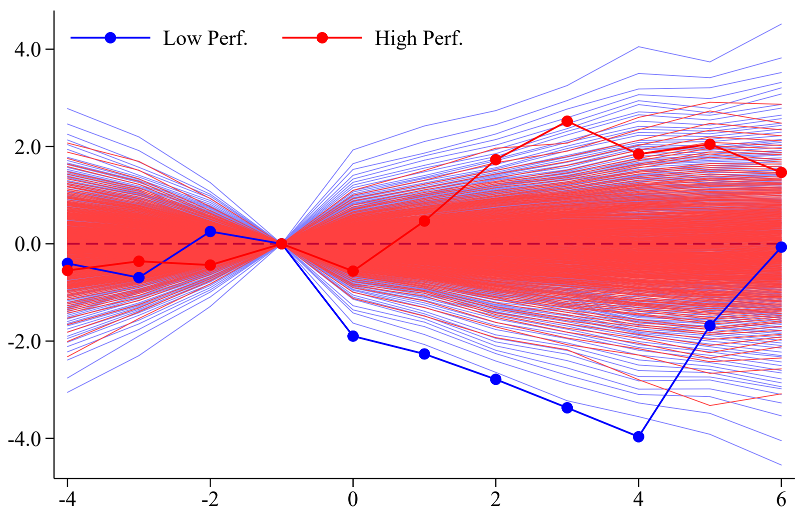
NOTE: This Figure presents estimates of β_1^h (scaled up by a 100 times an Interquartile Range shift of $\texttt{DISP}_{j,t}$)) from estimating this equation for $h \in \{-4, 6\}$: $\Delta COF_{a,t+h} = \sum_{x \in \iota}(\alpha^h_{1,x} X_{j,t} + \alpha^h_{2,x} X_{s,t-1} + \alpha^h_{3,x} X_{a,t-1} + \beta^h_{1,x}\texttt{DISP}_{j,t})\mathbf{1}_{a\in\iota} + \gamma^h_a + \gamma^h_t \times \gamma^h_k + \varepsilon_{a,t}$. 95% error bands are displayed in gray with standard errors clustered at the country level. The left panel includes the entire sample, the center and right panel includes, respectively, only the affiliates of parent companies which were in the bottom 40% (respectively top 40%) of the performance distribution the year before.

Figure A.6: Placebo Test: Whole Sample for all horizons



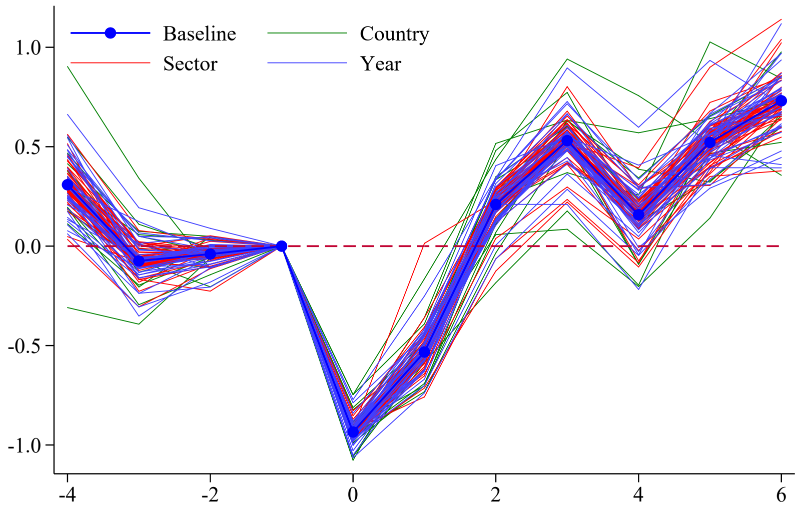
NOTE: This Figure presents 2000 estimates of the coefficient β_1 of our variable of interest $\texttt{DISP}_{j,t}$ (scaled up by a 100 times an Interquartile Range shift of $\texttt{DISP}_{j,t}$)) after performing a random permutation.

Figure A.7: Placebo Test: Low Perf. vs High Perf. for all horizons



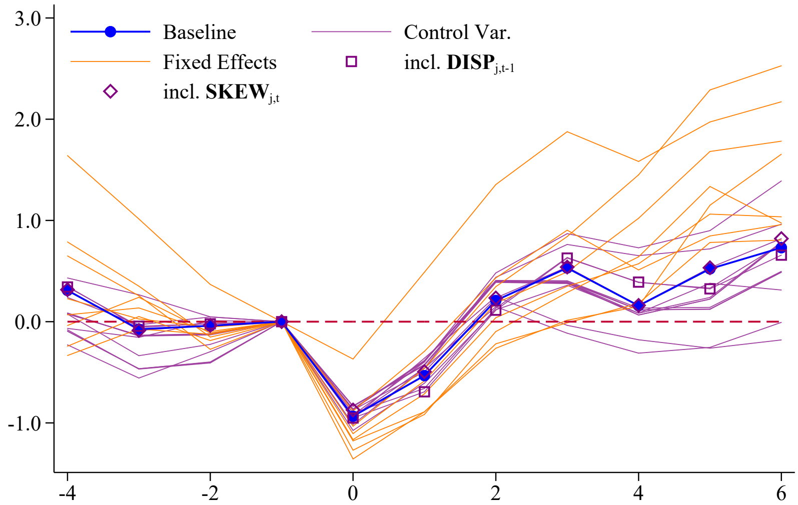
NOTE: This Figure presents 2000 estimates of the coefficient β_1 of our variable of interest $\texttt{DISP}_{j,t}$ (scaled up by a 100 times an Interquartile Range shift of $\texttt{DISP}_{j,t}$)) after performing a random permutation within each sub-sample.

Figure A.8: Cluster Sensitivity



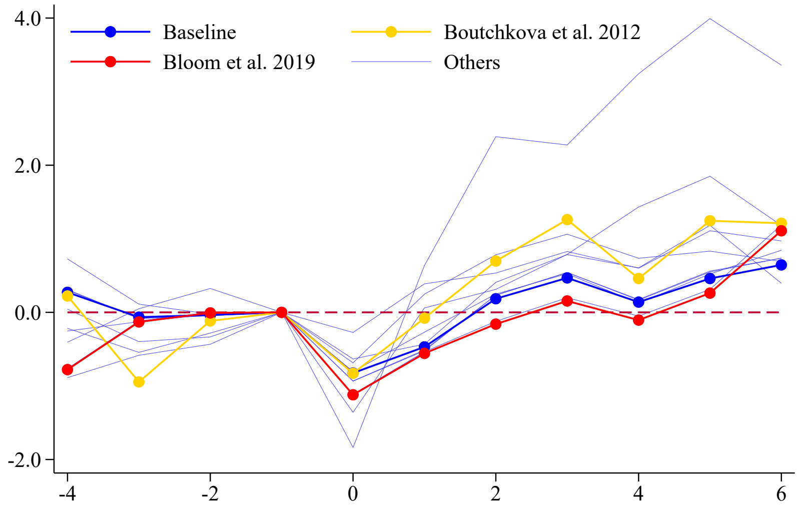
NOTE: This figure presents the distribution of the estimates of our coefficient of interest β_1 (scaled up by a 100 times an Interquartile Range shift of $\mathtt{DISP}_{j,t}$)) while removing any cluster of the main level of clusters in our sample (2-digit sectors in red, countries in green, years in blue).

Figure A.9: Specification Sensitivity



NOTE: The figure presents estimate of our coefficient of interest β_1 (scaled up by a 100 times an Interquartile Range shift of $\mathtt{DISP}_{j,t}$)) for various combinations of controls.

Figure A.10: 1st Stage Specification



NOTE: The figure presents estimate of our coefficient of interest β_1 (scaled up by a 100 times an Interquartile Range shift of $\texttt{DISP}_{j,t}$)) for various specification of the first stage.

Table A.3: Other Summary Statistics

Panel A Country-level	N	Mean	Median	Std.Dev.
Stock Price Volatility$_{j,t}$	514	22.55	21.00	9.22
Econ. Policy Unc.$_{j,t}$	220	117.21	111.63	43.56
Foreign Exchange Volatility$_{j,t}$	570	0.02	0.02	0.02
Macro FC ERR$_{j,t}$	529	2.31	1.91	1.92
Δ GDP$_{j,t}$	570	0.03	0.03	0.03
Δ FX$_{j,t}$	570	0.02	0.00	0.09
Trade Openness$_{j,t}$(*%GDP*)	570	99.48	73.52	84.31
GDP per capita$_{j,t}$	570	29658	27694	23122
Panel B Global				
Affilates per year	15	3894.27	3782.00	909.63
French Assets$_t$ (Bn.)	15	679.83	688.85	210.41
French Flows$_t$ (Bn.)	15	47.83	48.42	16.39

Stock Price Volatility (SPV), GDP and GDP per capita are from the World Development Indicators (WDI) database from the World Bank. We obtain daily exchange rates against the Euro from World Market Reuters and use it to compute yearly average and volatility measures. The VIX is the implied volatility index computed by the CBOE and EPU is the Economic Policy Uncertainty Index from Baker et al. (2016).

B Theoretical Explanation

This section provides an illustrative model to explain the effect of uncertainty shocks on foreign investments and accounting for heterogeneous responses of multinational firms. The model is based on the costly-state verification setup originally developed by Townsend (1979) and therefore incorporates in dynamic general equilibrium model by Bernanke et al. (1999). We follow the extension of this model by Christiano et al. (2014) who make uncertainty time-varying as the outcome of "Risk shocks". More precisely, we extend the partial and static equilibrium developed by Christiano et al. (2014) in their Appendix D to solve the market equilibrium for assets traded between domestic shareholders and multinational firms.

B.1 Assumptions

The model solves the partial market equilibrium for assets of domestic firms supplied by local shareholders to foreign investors. The supply of assets is decreasing with respect to the return yields, paid by local shareholders to foreign investors, according to

$$A^s = \overline{A} - \eta \times ROI \tag{1}$$

where $\overline{A} > 0$ is the inelastic supply of assets and $\eta > 0$ the elasticity of asset supply with respect to return yields, denoted ROI as in our empirical setup.

The demand for assets is the outcome of the maximization of expected returns by a continuum of multinational firms, which size is equal to one. To buy assets, they combine own capital, denoted N, and debt borrowed to financial intermediaries, denoted B. Then, the demand for assets A^d by the representative firm satisfies the financing constraint

$$A^d = N + B \tag{2}$$

In this static and partial equilibrium, capital N is treated as exogenous. The amount of debt B and the debt interest rate Z are however endogenous and determined by the optimal debt contract in the context of costly-state verification. Indeed, the multinational firm is exposed to an idiosyncratic shock on its return denoted ω. Idiosyncratic return shocks are distributed according to a lognormal distribution $F(\omega)$ which mean is equal to one, $E\omega = 1$, and the standard deviation of $\log(\omega)$ is σ. After realization of the shock, the return on assets is $\omega \times ROI$. There is a threshold $\overline{\omega}$ such that the multinational firm is unable to reimburse the debt if return shock ω is below this value: $\omega \leq \overline{\omega}$. The threshold value $\overline{\omega}$ satisfies

$$(1 + ROI)\,\overline{\omega} A^{d} = (1 + Z)\,B \tag{3}$$

and can be expressed as follows

$$\overline{\omega} = \frac{1+Z}{1+ROI}\frac{B}{A^{d}} = \frac{1+Z}{1+ROI}\frac{L-1}{L} \tag{4}$$

where $L = A^{d}/N$ is the leverage ratio. The threshold $\overline{\omega}$ and the default rate $F(\overline{\omega})$ are both increasing with the leverage ratio L and the ratio of debt interest rate to asset returns $(1 + Z)/(1 + ROI)$. Taking into account the default risk, expected returns are

$$\frac{\int_{\overline{\omega}}^{\infty}\left[(1+ROI)\,\omega A^{d} - (1+Z)\,B\right] dF(\omega)}{N(1+R)} \tag{5}$$

where R the risk-free interest rate accounts for the opportunity costs of investing capital N in assets instead of risk-free assets. Multinational firm earn profits only if they draw a return shock ω above the default threshold $\overline{\omega}$, otherwise the financial intermediary seize all assets and revenues.

The participation constraint of the financial intermediary to the contract writes as follows

$$\left[1 - F(\overline{\omega})\right](1+Z)\,B + (1-\mu)\int_{0}^{\overline{\omega}} \omega\,(1+ROI)\,A^{d} dF(\omega) = (1+R)\,B \tag{6}$$

With a probability $[1 - F(\overline{\omega})]$, the borrower does not default and reimburses debt and interests $(1 + Z)\,B$. In the case of default, the financial intermediary seizes the revenues from assets, namely $\omega\left(1+ROI\right)A^{d}$, but incurs monitoring costs which represent a share μ of these revenues. Financial intermediaries borrow at the risk-free interest rate R.

It is useful hereafter to consider the notation introduced by Bernanke et al. (1999) for $\Gamma\left(\overline{\omega}\right)=\overline{\omega}\left[1-F\left(\overline{\omega}\right)\right]+G\left(\overline{\omega};\sigma\right)$ which determines the sharing rule of revenues and $G\left(\overline{\omega}\right)=\int_{0}^{\overline{\omega}}\omega dF\left(\omega\right)$ which is the average return of defaulting entrepreneurs. The entrepreneurs receive the share $\left[1-\Gamma\left(\overline{\omega}\right)\right]$ of revenues while the financial intermediary gets only $\left[\Gamma\left(\overline{\omega}\right)-\mu G\left(\overline{\omega}\right)\right]$ since she supports the monitoring costs μ.

B.2 Equilibrium

The optimal debt contract is the set of variables $\{\overline{\omega},Z,B\}$ that maximizes the entrepreneur expected returns (5) subject to the participation constraint of financial intermediary (6) and the definition of the idiosyncratic return threshold (3).The equilibrium value of the threshold value $\overline{\omega}$ solves

$$\frac{1-F\left(\overline{\omega}\right)}{1-\Gamma\left(\overline{\omega}\right)}=\frac{\left[1-F\left(\overline{\omega}\right)-\mu\omega F'\left(\overline{\omega};\sigma\right)\right]\frac{1+ROI}{1+R}}{1-\left[\Gamma\left(\overline{\omega}\right)-\mu G\left(\overline{\omega}\right)\right]\frac{1+ROI}{1+R}} \tag{7}$$

Then, the amount of debt B is deduced from (6) and can be expressed as follows

$$L=\frac{1}{1-\left[\Gamma\left(\overline{\omega}\right)-\mu G\left(\overline{\omega}\right)\right]\frac{1+ROI}{1+R}} \tag{8}$$

Finally, (4) gives the loan interest rate Z

$$1+Z=\overline{\omega}\left(1+ROI\right)\frac{L}{L-1} \tag{9}$$

The definition of the equilibrium is as follows.

Definition 1. *The equilibrium is the set of variables* $\left\{\overline{\omega},Z,B,ROI,A^{s},A^{d}\right\}$ *which satisfies: the financial contract equilibrium equations: (7), (8), and (9); the supply of assets form the local shareholders (1) and the demand of assets by multinational firms (2); the market equilibrium for assets* $A^{s}=A^{d}$*; given the risk-free rate* R*, the capital of multinational firms* N*, the monitoring* *cost μ, the elasticity η and exogenous component $\overline{A}$ of the supply function of assets, the level of uncertainty σ, and the definition of the functions $F(\cdot)$, $\Gamma(\cdot)$, and $G(\cdot)$.*

B.3 Numerical simulations

We are interested in the impact of an increase in σ on the equilibrium. Unfortunately, it is not feasible to characterize analytically the effects on σ, then we use numerical simulations.

The monitoring costs and the level of uncertainty are taken from Christiano et al. (2014) (Appendix D): $\mu = 0.21$ and $\sigma = 0.26$. Then, the risk-free is set to 2%, $R = 0.02$, and we impose a return of 2% for assets taken from for our data, $ROI = 0.09$. Then, the following variables are deduced: the default risk is slightly above 10% ($F = 0.10$) and the leverage ratio more than three ($L = 3.59$). The supply elasticity of assets is set to one ($\eta = 1$), as the capital of multinational firms ($N = 1$), and we deduce $\overline{A} = 4.66$.

Figure B.11 shows the effect of increasing uncertainty σ in this model. Since multinational firm draw more extremely low values of idiosyncratic return shocks, there are more defaults in the economy as illustrated by the increase in F. Then, financial intermediaries ask for a higher interest rate Z to cover the higher monitoring costs and firms decrease their demand for debt and therefore their demand for domestic firm assets. As a results, the total investment in the domestic market for assets A decreases and the yield on these assets ROI increases as a compensation of the higher risk supported. Without considering fixed costs and extensive margin, but financial frictions, this model can therefore explain the negative average effect of uncertainty on FDI described in our empirical results. Can this model also explain the heterogeneity of the effects between multinational firms?

To investigate the effect of heterogeneity in this model, we assume that multinational firm differ with respect to the monitoring costs μ which takes now two values $\overline{\mu}$ and $\underline{\mu}$, with $\overline{\mu} > \underline{\mu}$. The population of firm, still normalized to the unity, is divided into two sub-populations of equal size. All firms have the same amount of wealth. Figure B.12 shows the effect of increasing uncertainty σ in this model. As in the case with homogeneous firms, there is an

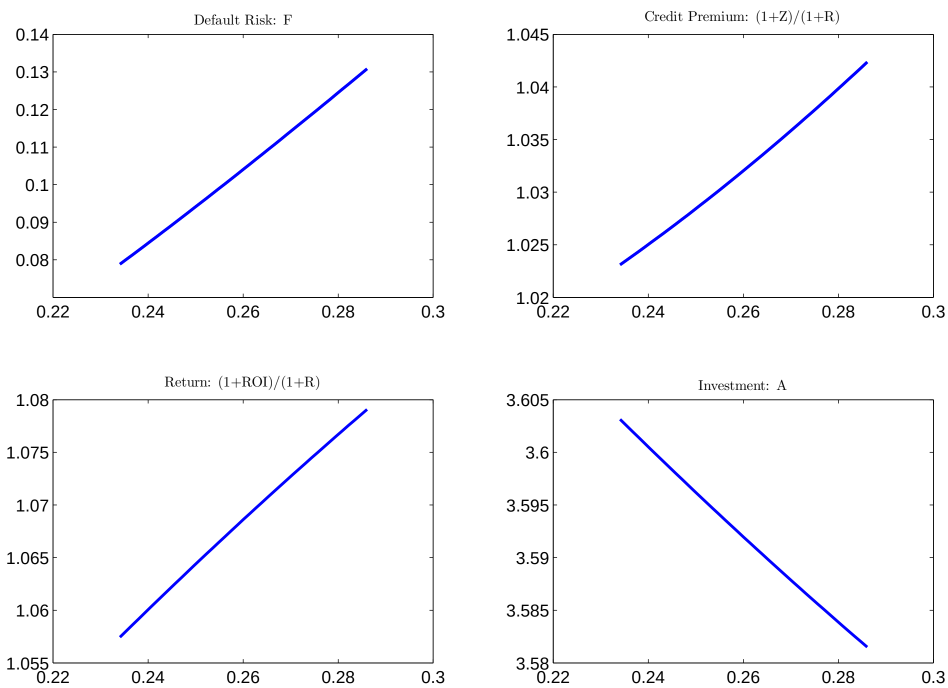


Figure B.11: Financial contract and market equilibrium for assets

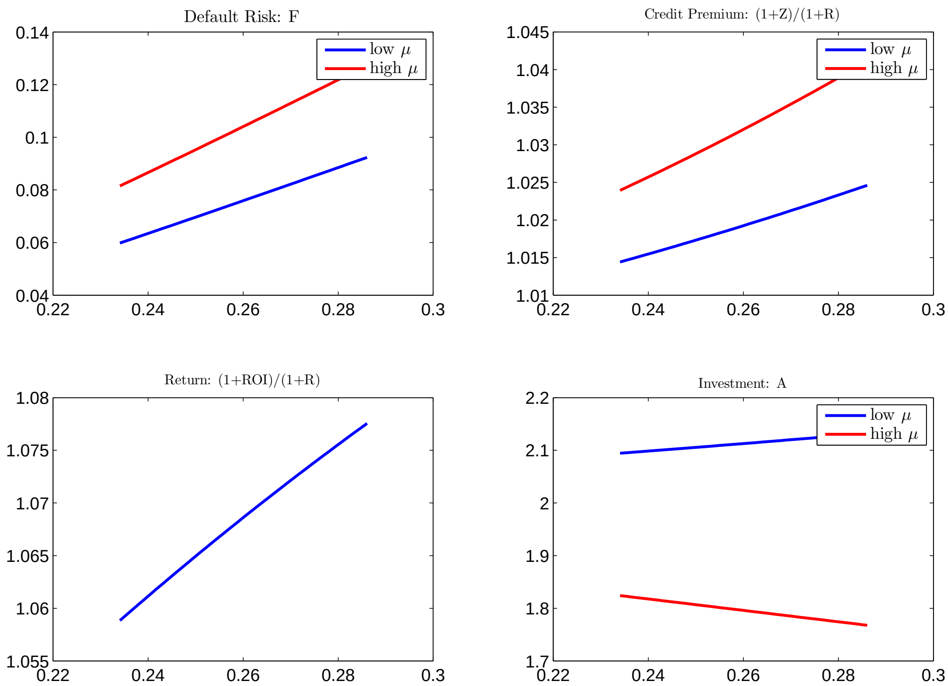


Figure B.12: Financial contract and market equilibrium for assets with heterogeneous multinational firms

increase in the default risk and in the risk premium for all firms and the fall in demand for domestic assets leads to an increase in the yields. The new fact is that we observe a divergence in investment. Firms with high monitoring costs decrease their investment while firms with low monitoring costs increase their investment. Firms with higher monitoring costs are more concern by the increase in uncertainty, since default is more costly for them, and therefore react more strongly than firms with low monitoring costs who get back market shares. Consistently with our empirical results the model describes a reallocation process of market shares between firms after an increase in uncertainty.

Chapter 3

Explaining the Persistent Effect of Demand Uncertainty on Firm Growth

In collaboration with Jean-Charles Bricongne

1 Introduction

The increase in cross-border trade and financial linkages since the 1990's has led to a greater exposure of domestic agents to shocks abroad. More firms are now dependent on inherently uncertain demand conditions. In this paper, we investigate how the uncertainty around the realization of demand shocks affects the growth dynamic of French manufacturing firms between 1996 and 2013. We build a measure of demand uncertainty by computing the dispersion of estimated demand shocks from the highly dis-aggregated BACI bilateral trade database. We then document the effect of an increase in demand uncertainty on employment and investment growth using French fiscal data. A striking result is the persistent negative effect of a one-time uncertainty shock. The effect lasts for several years for both investment and employment. It is not followed by a period of compensation which makes those losses permanent. We find that losses are magnified for financially constrained firms and firms with high correlation to their industry.

The starting point of our paper is to compute a firm-level measure that captures the uncertainty of demand shocks. Some studies use aggregate measures of uncertainty (Baker et al. (2016), Julio and Yook (2012) or Bussiere et al. (2015))). Others use stock market based firm-level measures (Bloom et al. (2007), Barrero et al. (2017) or Hassan et al. (2017)). We choose instead to measure uncertainty using the firm exposure to the dispersion of estimated foreign demand shocks. It has three distinct advantages. First, it allows us to focus on one properly identified form of uncertainty, i.e. demand uncertainty. Second, it provides an exogenous firm-level measure that we can causally link to the firm outcomes. Lastly, we obtain a wider and more representative sample than one obtained using publicly listed firms.

To compute this measure, we follow a recent strand of literature relying on the computation of foreign demand shocks. See Esposito (2018) for a review. Using the highly disagregated database BACI (Gaulier and Zignago, 2010), we first estimate `product`×`exporting-country`×`importing-country`×`year` idiosyncratic demand shocks. We then aggregate those shocks by measuring their mean and dispersion at the `sector` × `importing-country` × `year` level. We use the dispersion as a proxy for uncertainty. Exports from France are excluded to prevent endogeneity in the variations of those measures. To illustrate, the country-sector with the highest demand uncertainty in our sample is the manufacture of coke and petroleum in Nigeria in 2010 which coincides with the death of the sitting president and the beginning of the first major terror attacks by Boko Harram. We typically observe the highest values for other emerging countries (Mali, Syria, Central African Republic) in raw material transformation sectors (manufacture of wood, manufacture of other transport equipment, manufacture of paper, etc.). Finally, to obtain a firm-level measure, we use a weighting scheme instrument as in Aghion et al. (2017) and Mayer et al. (2016). We exploit differences in the firms' initial exposures to the mean and dispersion of shocks associated with their own sector in any given importing country. The mean represents the firm specific foreign demand, whereas the dispersion represents the firm specific uncertainty of this demand.

We then regress several outcomes related to firm growth (Employment, investment, debt, etc.) on this measure of uncertainty. We use Local Projections methods (Jordà, 2005) to assess the persistence of the effect of a one time change in uncertainty. Local Projections have recently been introduced for micro data where they provide a parsimonious and tractable alternative to VAR models to compute impulse response functions in the presence of potential non-linearities (see Favara and Imbs (2015), Crouzet et al. (2017) and Cezar et al. (2017)). We find that following a one standard deviation increase in uncertainty, firms lower their investment growth by -2.68 (s.e.= 0.541) percentage point and their employment growth by -2.16 (s.e.= 0.305) percentage point. The negative effect lasts for 5 years for investment and 5 years for employment. It does not exhibit any evidence of post-shock compensation (i.e. a positive value of the coefficient of uncertainty). Taken together, those results show that uncertainty has a permanent negative effect on firm growth. The contemporaneous slowdown of growth is consistent with the real-option theory. However, the persistence of the slowdown several years after the initial shock contrasts with the theory. The value of the option of waiting should only temporally increase while there is uncertainty about future outcomes. In this model, firms should then postpone investment and compensate once the uncertainty is resolved (Bernanke, 1983). Consistent with that, we find that firms who tend to experience similar uncertainty or sale dynamics to that of their industry revert back to their counter-factual growth rate within 1 to 3 years depending on the variable considered. However, firms with negatively correlated dynamics suffer from a much longer slowdown. In fact, capital growth does not seem to recover within our horizon window.

A tangential benefit of our approach of using foreign demand shocks is to allow us to measure the effect of the transmission of uncertainty abroad on the growth of domestic firms. Our study contributes to the debate of the effect of trade on firm dynamics. Many studies have now documented the importance of idiosyncratic demand shocks to aggregate fluctuations. Garin et al. (2017) investigate the impact of idiosyncratic foreign demand shocks on firm output and workers individual wages. di Giovanni et al. (2017) show how idiosyncratic shock drives aggregate fluctuations through large firms. Hummels et al. (2014) find that an exogeneous rise in foreign demand increases employment and wages for both skilled and non skilled workers. Other studies have focused on how idiosyncratic shock uncertainty affects exporters' behavior. It leads to lower than optimal size of supplier to allow for diversification (Gervais, 2018). Only large firms really benefit from diversification opportunities (Vannoorenberghe et al., 2016). While Esposito (2018) shows that risk diversification leads to wellfare gains. Vannoorenberghe (2012) shows that higher export share implies higher volatility of domestic sales. De Sousa et al. (2016) find that expenditure uncertainty reduces exports. Especially, more productive firms tend to abandon market shares in volatile destinations to less productive firms. Our study complements those results by showing that losses caused by a 2^{nd} moment shock (i.e. higher uncertainty) may potentially offset gains from a 1^{st} moment shock (i.e. higher demand). We show that the uncertainty of demand has long lasting consequence for the growth of manufacturing firms. The failure to take into account demand uncertainty could lead to overestimating gains from trade.

The reminder of the paper is organized as follows. Section 2 describes the data and our methodology to compute the uncertainty of idiosyncratic demand shocks. We show some stylized facts motivating our methodological choice in Section 3. Section 4 provides our empirical results regarding the effect of uncertainty on firm growth. We show the robustness of our results in Section 5. Section 6 concludes.

2 Data

In the following subsections, we describe our data sources as well as the computation of our measure of Demand Uncertainty.

2.1 Data Sources

We build a database of matching fiscal, export and employment benefit data of French firms between 1995 and 2013. We use export data from the French customs database to compute firm-level exposure to foreign demand shocks and uncertainty. Firm accounting data come from the French fiscal database FARE and FICUS. We use it to compute most of our control (eg. productivity, cash flow, etc.) and dependent variables (investment, employment). It also provides us with the firm primary sector of activity. Employee level data comes from the annual social data declaration DADS. It allows us to decompose how firms arbitrage between work-force size, structure and wages. It contains one observation per work contract with information regarding the type of contract and various employee (age, gender, etc.) plus firm characteristics (size, county, etc.). We calculate individual hourly wage growth rates then we average them at the firm level. We use LIFI to control whether the firm belongs to a group. We use BACI (Gaulier and Zignago, 2010) to compute import demand moments, including our uncertainty proxy. BACI is a product-level bilateral trade database maintained by the CEPII. Finally, we collect various country characteristics from the World Bank, the International Monetary Fund and a few other ancillary sources. We present summary statistics in Table 1. We follow about 30000 firms for 17 years including firms that enter late or exit early in our sample.

Table 1: Firm characteristics

Outcome Variables	Mean	Std.Dev.	P25	P50	P75
Δ Capital$_{f,t}$	0.019	0.510	-0.149	-0.030	0.114
Δ Tangible K$_{f,t}$	0.009	0.511	-0.186	-0.046	0.127
Δ Intangible K$_{f,t}$	0.017	0.904	-0.151	0.000	0.057
Δ Debt$_{f,t}$	0.034	0.335	-0.120	0.016	0.176
Δ Employment t$_{f,t}$	-0.001	0.294	-0.052	0.000	0.061
Δ Employment t$_{f,t}$	-0.005	0.467	-0.067	0.000	0.071
Δ white-collars$_{f,t}$	0.013	0.433	-0.105	0.000	0.154
Δ blue-collars$_{f,t}$	0.002	0.417	-0.102	0.000	0.114
Control Variables					
Log Total Assets$_{f,t}$	8.348	1.765	7.110	8.188	9.402
Log Non Financial Capital$_{f,t}$	5.972	2.140	4.585	5.889	7.303
$\sharp$ Employees$_{f,t}$	104	428	11	28	71
Log Total Sales$_{f,t}$	8.413	1.688	7.244	8.291	9.439
Log Value Added$_{f,t}$	7.273	1.614	6.201	7.190	8.224
Log Productivity$_{f,t}$	3.845	0.589	3.534	3.830	4.147
$\frac{Debt_{f,t}}{A_{f,t-1}}$	0.436	0.271	0.275	0.405	0.558
$\frac{CashFlow_{f,t}}{A_{f,t-1}}$	0.077	0.145	0.017	0.054	0.102
$\frac{ForeignSales_{f,t}}{TotalSales_{f,t}}$	0.247	0.263	0.038	0.141	0.387
Variable of Interest					
Demand Uncertainty$_{f,t}$	0.046	0.102	0.006	0.016	0.041
Observations	303363				

NOTES: All outcome and control variables are computed using either fiscal (FARE, FICUS, DADS) or custom databases. The variable of interests was computed using the bilateral product level database BACI. See Section 2.2 for the construction of the moments of the distribution of demand shocks. f and t indexes firms and years respectively.

2.2 Demand shocks and Uncertainty

The first step is to isolate demand shocks in the bilateral trade data. We follow a methodology similar to Garin et al. (2017) and Esposito (2018). We have a set of countries J that import a set of products P from a set of countries $I \setminus \{i = FRA\}$. Let $V_{p,i,j,t}$ be the imports of product p from country i by country j in year t and $\Delta V_{p,i,j,t}$ be its log 1st difference. Then $\upsilon_{p,i,j,t}$ is the idiosyncratic demand shock, computed as the residual of estimating the following equation:

$$\Delta V_{p,i,j,t} = \underbrace{\gamma_{p,i,t} + \gamma_{p,j,t}}_{\text{Market Fundamentals}} + \underbrace{\upsilon_{p,i,j,t}}_{\text{Idiosyncratic Demand Shock}} \tag{1}$$

The intuition behind this 1^{st} stage is the following[1]. The fixed effect $\gamma_{p,j,t}$ absorbs any variation in imports of product p from country j that are common to all exporting countries. We are interested in the specific demand from j to i relative to that aggregate fluctuation. All other things equal, the greater the residual $\upsilon_{p,i,j,t}$, the more j wants p from i as opposed to p from the rest of the world $I \setminus \{i\}$. This residuals still contains fluctuations generated by supply shocks in exporting country i but common to all importing countries. To remove this variance, we add the fixed effect $\gamma_{p,i,t}$ to the specification.

The residuals $\upsilon_{p,i,j,t}$ are by construction the variance that cannot be explained by either market fundamentals. Their dispersion informs us on the noisyness of the demand signal, that is how uncertain the signal would appear to an outside observer. We use this variable as our time varying proxy for demand uncertainty in a given market. A market is a set of products (Harmonised System-6 digit) imported by a narrow sector (NACE-3 digit) from the rest of the world. We follow Bardaji et al. (2019) to match the BACI product codes to the sectors in the NACE nomenclature. We allow a product to be matched to different sectors. We keep only destination markets (country × NACE 3-digit) for which we have at least 15 different HS6 products and/or source country. Let $\upsilon^{pc}_{k,j,t}$ be the $\mathtt{pc}^{th}$ percentile of the distribution of all $\upsilon_{h,i \neq FRA}$

[1]We thank Anne-Laure Delatte for pointing out that this step can also be thought of as a generalization of the estimation of liquidity shocks in Khwaja and Mian (2008).

for each sector-importer-year (k, j, t). Let $D^{IQR}_{k,j,t}$ be the interquartile range of the distribution of the idiosyncratic demand shocks of product p from sector k and country i (excluding France) into country j:

$$\text{Dispersion: } D^{IQR}_{k,j,t} = \upsilon^{75}_{k,j,t} - \upsilon^{25}_{k,j,t} \tag{2}$$

This step provides a robust and intuitive measure of the dispersion of demand shocks. The higher the value of $D^{M2}_{k,j,t}$, the wider the distribution and the nosier the signal. We compute alternative measures using the standard deviation of the residuals, the spread between $\upsilon^{10}_{k,j,t}$ and $\upsilon^{90}_{k,j,t}$ or $\upsilon^{5}_{k,j,t}$ and $\upsilon^{95}_{k,j,t}$ and confirm that our results remains virtually unchanged. Throughout this paper, we use the interquartile range measure as our baseline because it is known to be more robust to outliers than its alternatives. This helps mitigate the effects of some very volatile and intermittent trade flows such as a one time order for a luxury yacht in the Caiman Islands.

We now transform our sector-country-year measure into a firm-year specific variable. We follow the standard method in the literature (See Aghion et al. (2017), Mayer et al. (2016) or Berthou and Dhyne (2018)). We weight the dispersion of demand shocks by the firm initial market share and export intensity. In our baseline specification, to reduce the impact of the partial year effect, we use the average of the first three periods. Omitting to do so would likely lead to underestimate the trade exposure of the firm (see Bernard et al. (2017)). We also employ weights based on the first year only and show that our main results still hold and we document the robustness to other potential weighting schemes (sectoral, aggregates, etc) in Section 5. The weights are necessary to account for the across firms variations in market diversification. In all cases, the observations used to compute the weights are not re-used in the subsequent estimations. Thus by using the initial firm weights, we ensure that any across time fluctuations in the firm level measure are only caused by variations of the demand uncertainty measure and not by any endogenous firm reaction. We will provide some evidence of this in Section 3.2.

Concretely, we first compute the initial period country weight by taking the average of the first three years of the firm exposure to each of its export market:

$$\omega_{j,f,t_3} = \frac{1}{J^f} \sum_{j=1}^{J^f} \frac{1}{3} \sum_{t=0}^{2} \left(\frac{X_{j,f,t}}{X_{f,t}} \right) \tag{3}$$

We then compute the initial period export intensity (the stars indicate the use of fiscal data rather than custom data for this step), once again by taking the average of the export intensity of the first three years:

$$\omega_{f,t_3} = \frac{1}{3} \sum_{t=0}^{2} \frac{X^*_{f,t}}{Y^*_{f,t}} \tag{4}$$

Finally, in equation (5), we assign to the firm the level of uncertainty of its self declared primary sector of activity (at the NACE-3 digit level) in all of its export destinations which we then combine with the weights computed above to obtain our firm-level measure of uncertainty:

$$D^{IQR}_{f,t} = \underbrace{\omega_{f,t_3}}_{\substack{\text{Export}\\\text{ntensity}}} \times \underbrace{\omega_{j,f,t_3}}_{\substack{\text{Country}\\\text{weight}}} \times D^{M2}_{k=k_f,j,t} \tag{5}$$

3 Stylized Facts

In this subsection, we show (1) that the dispersion of demand shock is a useful proxy for uncertainty and (2) that our weighting scheme provides plausible exogeneity.

3.1 Demand Uncertainty

We start by illustrating some facts about the measure of demand uncertainty. We computed over 322 thousands value of uncertainty for all 109 NACE-3 digit manufacturing sectors in 217 countries for 20 years. Table 2 reports the 10 highest value of Demand Uncertainty in our sample. For instance, the country sector with the highest value is the Manufacture of steam generators in Timor in 2007. It coincides with a coup d'état and a foreign military intervention. The second one is the Manufacture of communication equipment in Cambodia in 2005 which saw the leader of the opposition fleeing the country. The third highest one is the Manufacture of tanks, reservoirs, etc in Congo in 2011 in the context of a disputed presidential elections.

Table 2: Top 10 uncertain markets

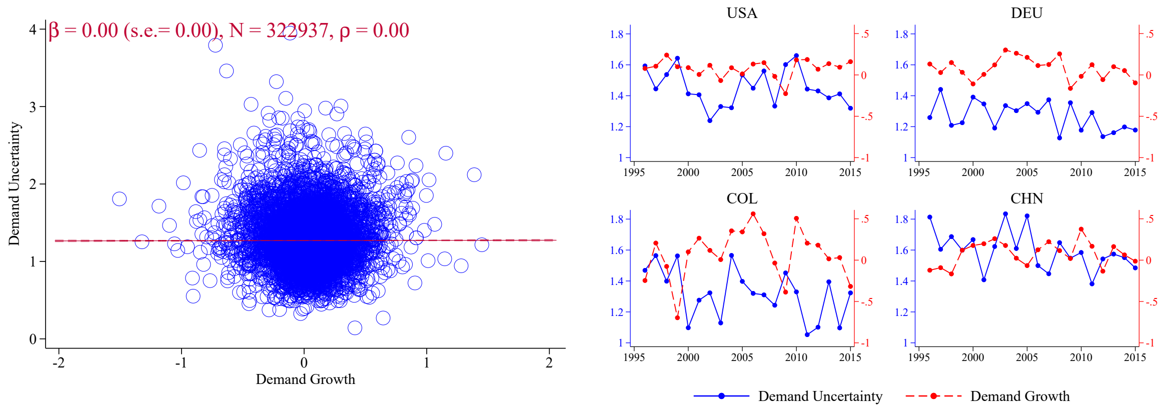
	Demand Uncertainty
1999 - Croatia - Manufacture of steam generators, except cen (...)	4.18
2005 - Cambodia - Manufacture of steam generators, except ce (...)	4.57
2007 - Timor - Manufacture of communication equipment	4.63
2009 - Algeria - Manufacture of steam generators, except cen (...)	3.98
2009 - Chad - Manufacture of structural metal products	4.03
2010 - Chad - Manufacture of structural metal products	4.01
2011 - Congo - Manufacture of tanks, reservoirs and containe (...)	4.43
2011 - Ethiopia - Manufacture of steam generators, except ce (...)	4.36
2011 - Madagascar - Manufacture of tanks, reservoirs and con (...)	3.98
2013 - Djibouti - Manufacture of refractory products	4.33

In Figure 1b, we plot the dispersion of the idiosyncratic demand shocks computed in the previous section for the manufacture of motor vehicle ($k = 291$) for four countries (USA, Germany, Colombia and China). In this paper, we exploit those time and geographical variations in the uncertainty of demand shocks to identify them. For reference, we also plot the growth rate of the raw imports of each of those market in red. Disentangling first moment from second moment shock is one of the key challenge of the uncertainty literature. In Figure 1a, we show that there is no correlation between demand uncertainty and import growth. This fact will help us properly identify the effect of demand uncertainty in Section 4. Although there is no obvious counter-cyclicality in the right panel, we do see some increase uncertainty and lower import growth around the time of the Asian crisis, around the 2001 recession and again around the time of the Great Financial Crisis.

In Figure 2, we plot demand uncertainty averaged at the country-year level against log GDP per capita as well as some variables related to aggregate risk or uncertainty. We find a negative relationship between demand uncertainty and GDP per capita as is typically expected in the litterature (Bloom (2014)). However, for each level of economic development, there is ample variations in terms of uncertainty. When we compare our measure against other known proxies, we generally find a positive slope (from 0.14 to 0.62), significant at the usual reference levels. This shows that the dispersion of idiosyncratic demand shocks likely incorporates some ele-

Figure 1: Demand Growth and Demand Uncertainty

(a) Demand Growth and Demand Uncertainty **(b)** for the motor vehicle industry (1996-2015)



NOTE: The left sub-figure presents a scatter-plot of the relationship between raw import growth and demand uncertainty. For obvious reasons, only 5% of the sample is plotted. The right sub-figure shows the time series of import growth and demand uncertainty in the motor vehicles industry ($k = 291$) in 4 countries. See Section 2.2 for the construction method.

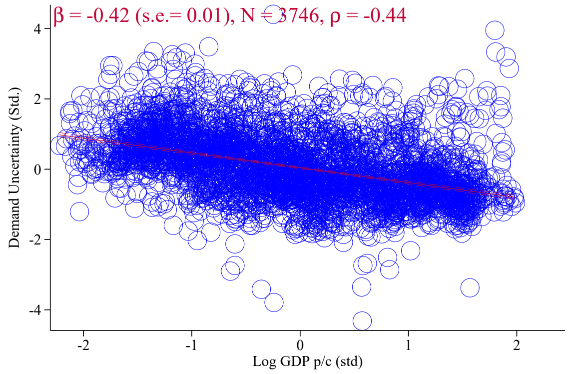
ments common to those measures of volatility while not being completely related to any single one.

3.2 Weighting Scheme

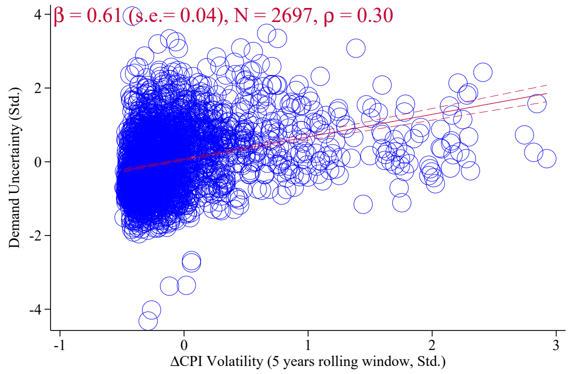
As stated in Section 2.2, we use the initial firm weights which ensure that any across time fluctuations in the firm level measure are only caused by variations of the demand uncertainty measure and not by any endogenous firm reaction. The reader will note that we do not claim that firms do not self select into foreign market based on a combination of firm level characteristics and market uncertainty. Works by Héricourt and Nedoncelle (2016) and De Sousa et al. (2016) show that such selection is likely happening. Our claim however is that this self selection based on factors such as initial productivity and initial uncertainty is unrelated to future fluctuations in Demand Uncertainty. To support that claim we show in Figure 3d that $D^{M2}_{j,k,t}$ has no auto-correlation left beyond two years ($h = 2$). So even if the firm took into account the initial level of uncertainty to choose to enter a destination, this initial uncertainty is unrelated to its future levels. To further validate this claim, we show in Figures 3a and 3b the absence of correlation between future level of uncertainty and either initial productivity or size. In those two figures, we plot respectively the initial value of the log of the ratio of value added over the number of employees and the log of initial total gross assets against the median value of future firm-level uncertainty $D^{M2}_{f,t>1}$. A further risk to our identification strategy would be that initial weights are a poor predictor of future weights. We show in Figure 3c that weights exhibits auto-correlation for up to 10 years.

Figure 2: Uncertainty and Other Variables

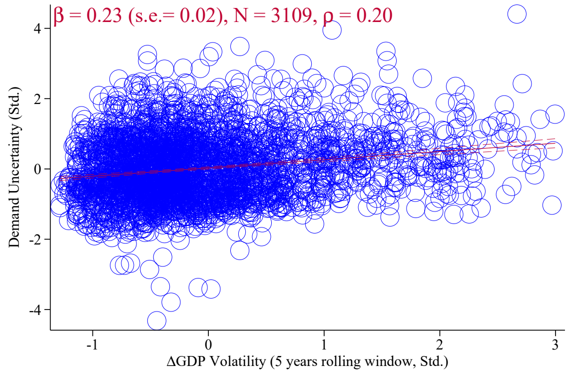
(a) Uncertainty and Development



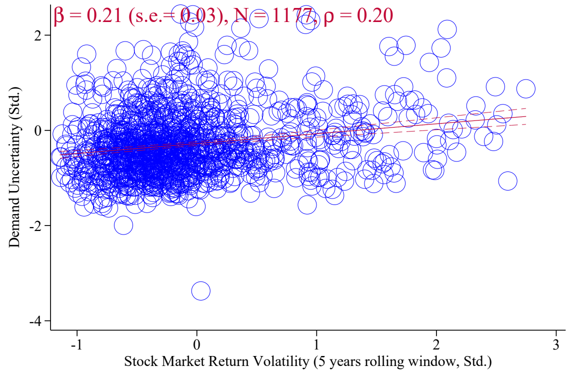
(b) Inflation Volatility



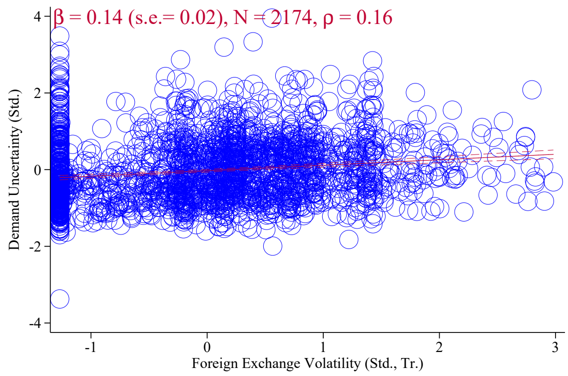
(c) GDP growth volatility



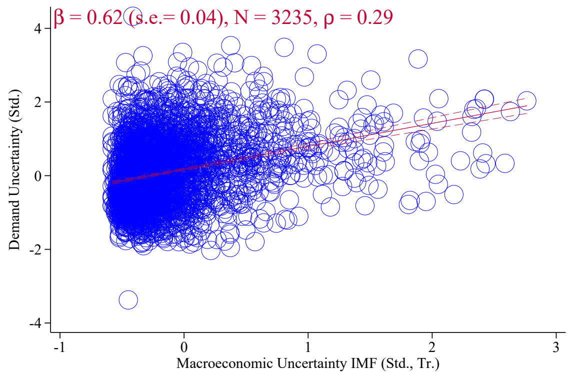
(d) Market Return Volatitity



(e) Foreign Exchange Rate Volatility



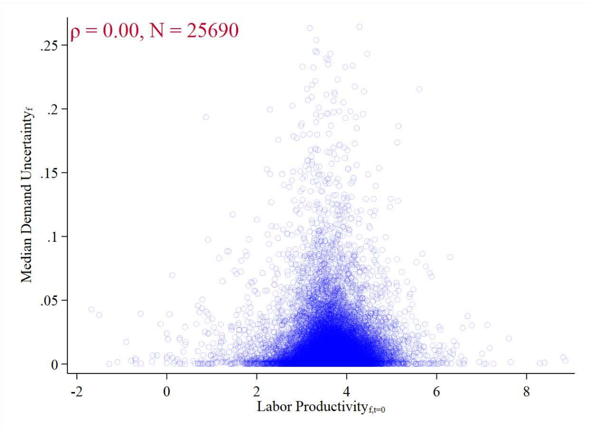
(f) IMF Dispersion of the WEO Forecast Errors



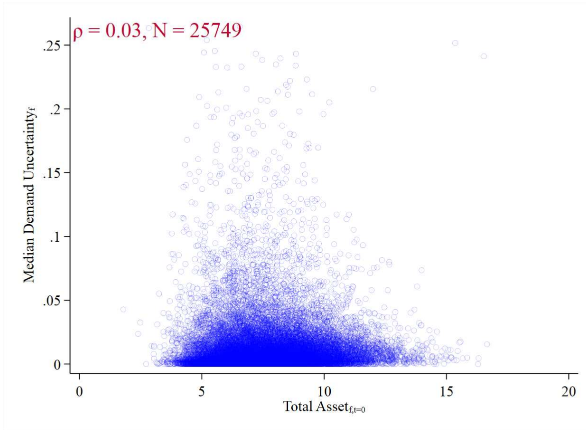
NOTE: We plot demand uncertainty averaged at the country-year level against log GDP per capita as well as some variables related to aggregate risk or uncertainty. Std. indicates the variable was demeaned and normalized by its standard deviation, Tr. that it was trimmed at the 99th percentile. See Section 2.2 for the construction method of Demand Uncertainty.

Figure 3: Uncertainty, weights and initial characteristics

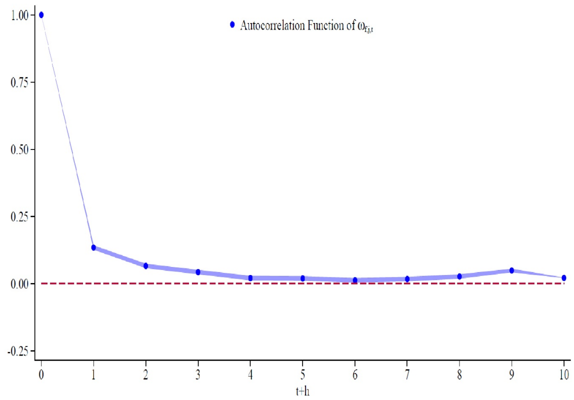
(a) Uncertainty and Initial Productivity



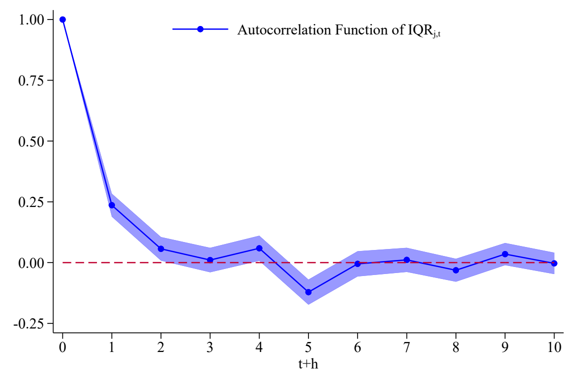
(b) Uncertainty and Initial Asset Size



(c) Destination Weights ACF



(d) Uncertainty ACF



NOTE: See Section 2.2 for the construction method of Demand Uncertainty. Labor productivity is computed as the log of the ratio of value added over the number of employees. Asset size is computed as the log of total gross assets.

4 Impact of Demand Uncertainty on Firm Growth

In this section, we first provide estimates of the firm growth path around an increase in demand uncertainty using local projections. We then show how comovement in the industry affects the reaction of the firm to uncertainty and help explain its apparent persistence.

4.1 Baseline Regressions

We use the Local Projections (LP) method as in Jordà (2005) to recover the dynamic effect of demand uncertainty on firm growth. We estimate its impact at up to 6 years after the initial impulse and 6 years prior. Our variable of interest is the level of Demand Uncertainty: $D^{IQR}_{f,t}$. Let:

$$G_{f,t} = \{Capital, Employment\}$$

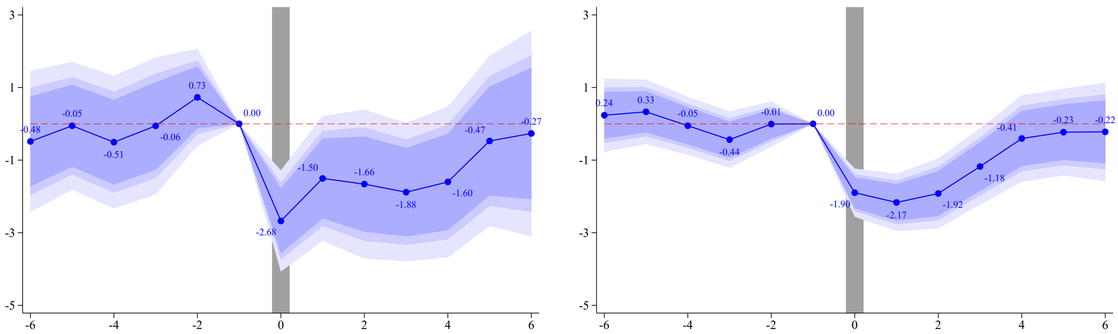
then:

$$\Delta G_{f,t+h} = \log\left(\frac{G_{f,t+h}}{G_{f,t-1}}\right) = \alpha_{\mathbf{1}}^{\mathbf{h}}\mathbf{X_{f,t-1}} + \beta_1^h D^{IQR}_{f,t} + \gamma^h_{k,t} + \gamma^h_f + \epsilon_{f,t+h} \tag{6}$$

for $h \in \{-6, 6\}$ and where $\Delta G_{f,t+h}$ denotes the cumulative change in outcome variable G from time t to $t+h$. We use the log difference as in Bloom et al. (2007). We add a vector of lagged firm-level controls $\mathbf{X_{f,t-1}}$. By default, we include the lagged level of sales to control for the initial size and two lags of the level of demand uncertainty ($D^{IQR}_{f,t-1}$) to control for its small amount of auto-correlation illustrated in Figure 3d. Following Goldsmith-Pinkham et al. (2018), since the shares used to compute the firm-level uncertainty do not sum to one, we add a control for the initial share interacted with a year trend. Removing this variable does not alter our results (see 5). We add futher control variables to capture relevant firm characteristics for growth (e.g. Gilchrist and Himmelberg (1995), Bloom et al. (2007) and Gala and Julio (2016)) in the robustness section. We add a firm fixed effect to capture the time-invariant heterogeneity of firm dynamics. Finally, we add a sector-time fixed effect to capture the sector business cycle. The effect we identify is therefore that of a within firm unit change in demand uncertainty in deviation of the current sectoral conditions. We cluster the standard errors at the sector-level to account for potential within sector correlation in the error term (Bertrand et al., 2004)[2]. Overall, our specification is almost identical to that of Carluccio et al. (2018) with a similar empirical set-up.

Figure 4: Demand Uncertainty and Firm Growth

(a) Investment **(b)** Employment



NOTE: Those figures present estimates of the coefficient $\beta_1^h * 100$ associated with demand uncertainty from estimating this equation: $\Delta G_{f,t+h} = \alpha_1^{\mathbf{h}} \mathbf{X_{f,t-1}} + \beta_1^h D_{f,t}^{IQR} + \gamma_{k,t}^h + \gamma_f^h + \epsilon_{f,t+h}$. 90%, 95% and 99% error bands, computed with robust standard errors clustered at the sector-level, are displayed in shades of blue. The size of the shock is set at one standard deviation. E.g.: a one standard deviation uncertainty shock decreases investment growth by 0.45 percentage point the year of the shock.

We report the results of estimating the β_1^h coefficients in Figure 4. We show the effect of a one-standard deviation increase from the mean value of $D_{f,t}^{IQR}$ for investment and employment relative to the year before the shock. Both outcomes exhibit little anticipatory response to the shock.

On the left panel of Figure 4, the impact on the stock of non financial capital is negative during the seven years following the increase in uncertainty. However, only the coefficient for the first year is statistically significant at the 99^{th} percent level. Then the coefficient remains significant for four more years (until $h = 4$) at the 95^{th} percent level. It then reverts back to approximately zero for the remaining two years of the projection window. A standard deviation size increase in uncertainty results in a contemporaneous 2.68 log percentage point lower growth rate of investment (compared to a sample mean growth rate of 1.9%). Four years later, this increase still results in a 1.60 p.p. lower growth rate.

[2]Other reasonable levels of clustering such as sector × year or firm provide standard errors of similar sizes. We also provide non-parametric confidence bands in Section 5.

The effect on employment growth follows essentially the same pattern. It remains negative until the end of the estimated response function while it slowly reverts back to zero. It remains significant at the 99^{th} percent level for four years ($h \in \{0, 3\}$) The contemporaneous effect is equal to 1.90 percentage point lower growth rate (compared to a sample mean of approximately 0%) Its effect is still -1.18 p.p. three years later ($h = 3$). We show in Figure A.0.14 that using the standard deviation rather than the interquartile range to compute the dispersion of demand shocks does not alter meaningfully our results.

The greater contemporaneous response of capital expenditure compared to employment might suggest that firms decreases their capital to labor ratio. However when estimating the response path of this ratio, we only find a small and noisy effect for $h = 0$ (not reported).

Figure A.0.13 presents the result from the same specification on other outcome variables. This allows us to perform a few sanity checks. First, we decompose capital growth into tangible and intangible asset acquisitions. The response function of intangible capital growth is particularly noisy compared to tangible growth. This helps explain the noisiness of the effect we observed for overall capital growth. The pattern of the coefficients for $h < 0$ illustrates the need to check for pre-trends when performing Local Projections [3]. The size of the coefficients is greater before the uncertainty shock than after. It makes the post-shock impulse response function impossible to interpret. Second, we look at the effect on debt growth. We find it follows a pattern similar to the effect on investment but much more precisely estimated. We confirm the pattern and magnitude of our result on employment by using data from the DADS social declarations rather than from the fiscal declarations. We can also confirm that using the DADS data generates standard errors of similar size to those computed with the fiscal data. Our result is therefore unlikely to be an artifact of the way firms estimate and report their employment to the French Treasury. We also find that the employment of white-collar workers is somewhat more persistent to uncertainty than the employment of blue-collar workers.

This persistent negative effect from a one time increase in uncertainty contrasts with the wait-and-see effect predicted by the literature. We now examine potential explanations. In the

[3] To our knowledge Zidar (2019) and Cezar et al. (2017) are the only articles performing such a check.

next section, we show that this persistence

4.2 Sectoral Comovement and the Persistent Effect of Uncertainty

Cezar et al. (2017) shows the existence of a long lasting reallocative effect from the lower performing multinationals to the better performing ones. They argue that multinationals are competing against one another for access to external finance. Uncertainty crowds out lower performing firms that exhibits higher monitoring cost to the benefit of better performing ones. If this explanation holds true, firms facing business conditions similar to those of the rest of their industry should be less affected than firms facing different conditions from the rest of their industry. To put it differently, an idiosyncratic shock should have a bigger bite on the small number of affected firms than an aggregate shock should have on each firm in the entire industry. In the case of an idiosyncratic shock, unaffected firms will face less competition on both their input and output market. This should compound the effect on the uncertainty shock.

We build three measures that capture key aspects of firm-sector comovement and interact them with firm-level uncertainty. First, we simply compute a measure of average sectoral (NAF 3-digit) uncertainty while excluding the firm itself. This means that for each observation (firm $\times$ year), we have a firm specific measure of the uncertainty in its sector. We expect uncertainty to have a lower impact when uncertainty among its potential competitor is high. Second, we build a measure of the co-movement of the firm uncertainty with that of its sector. Firms that typically face uncertainty similar to that of their sector should exhibit a lower sensitivity to an increase of their own uncertainty. Finally, we compute a similar measure but with sales instead of uncertainty. Firms that on average experience sales growth close to that of their industry should also have a lower sensitivity to higher uncertainty.

We follow Guiso and Parigi (1999) to construct our measure of firm-industry covariance. We compute the correlation between the growth rate of the firm's sales and the growth rate of the sales of its industry. Formally, we compute for each firm-year the average of the growth rate of sales for all other firms in the industry. Then, we compute the pearson correlation coefficient

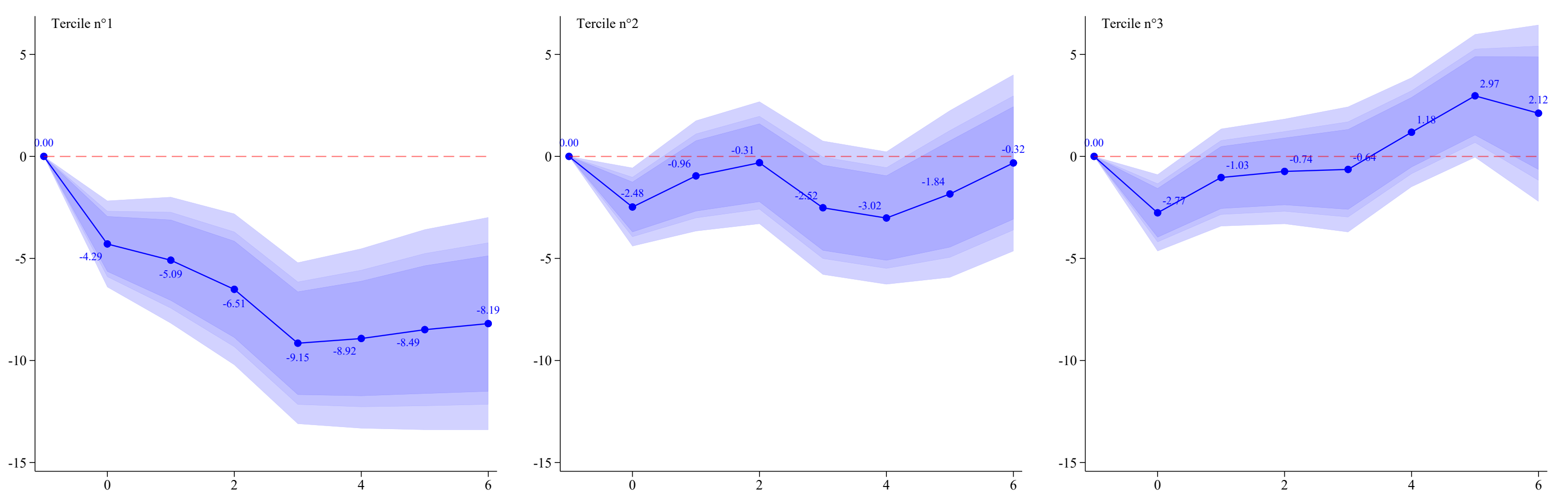
$\rho_f^Y = \rho(\Delta Y_{f,t}, \Delta Y_{k_f \setminus f,t})$. This measure is bounded between $\{-1, 1\}$. We repeat the same procedure for the level of uncertainty ρ_f^{IQR}. We then estimate the effect of uncertainty for each tercile of the measure of sectoral uncertainty and for each intervals $[-1, -0.1[$, $[-0.1, 0.1]$ and $]0.1, 1]$ for the firm-sector correlation measures. This allows each bin to have its own slope with respect to a unit change in uncertainty. The measures of correlations are not time-varying so their direct effect is absorbed by the firm fixed effect.

We plot the coefficients of the interaction of each tercile of sectoral uncertainty with the baseline measure of firm-level uncertainty in Figure 5. The contemporaneous response for firms in a sector-year with relatively low uncertainty is much stronger than the baseline for both investment and employment (-4.29 p.p. and -3.68 p.p. against respectively -2.68 p.p. and 1.90 p.p.). Additionally, whereas the middle and top tercile recover within 1 to 3 years, the losses for the bottom group appear permanent within our time window.

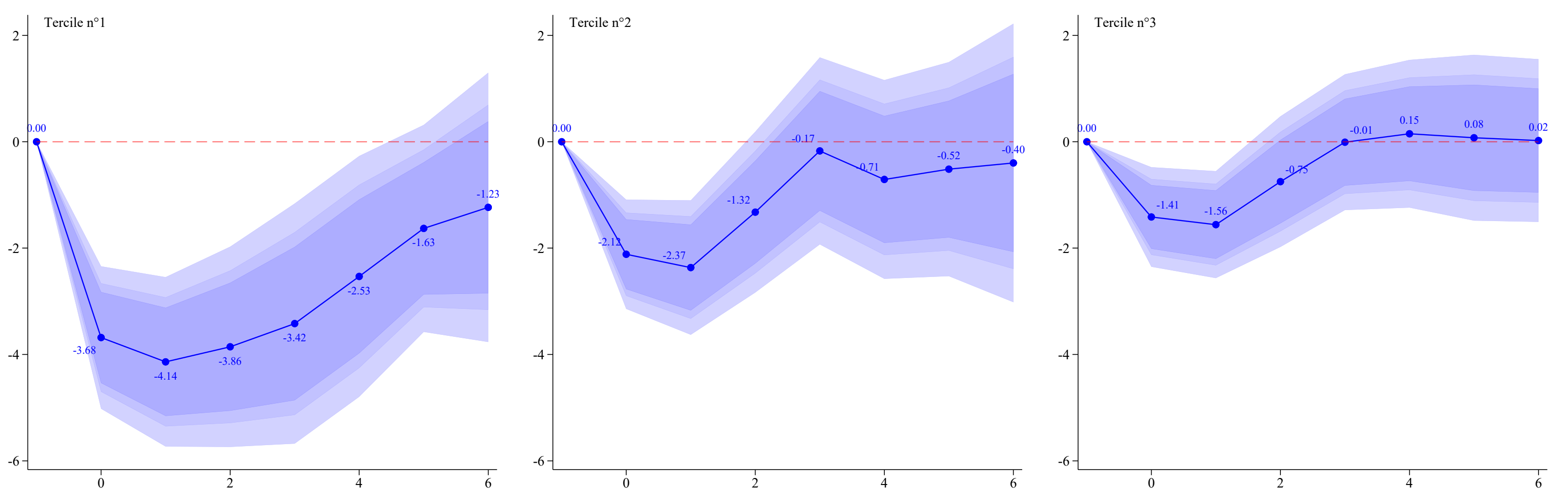
Figure 5: Sectoral Uncertainty

Low → Medium → High

(a) Investment



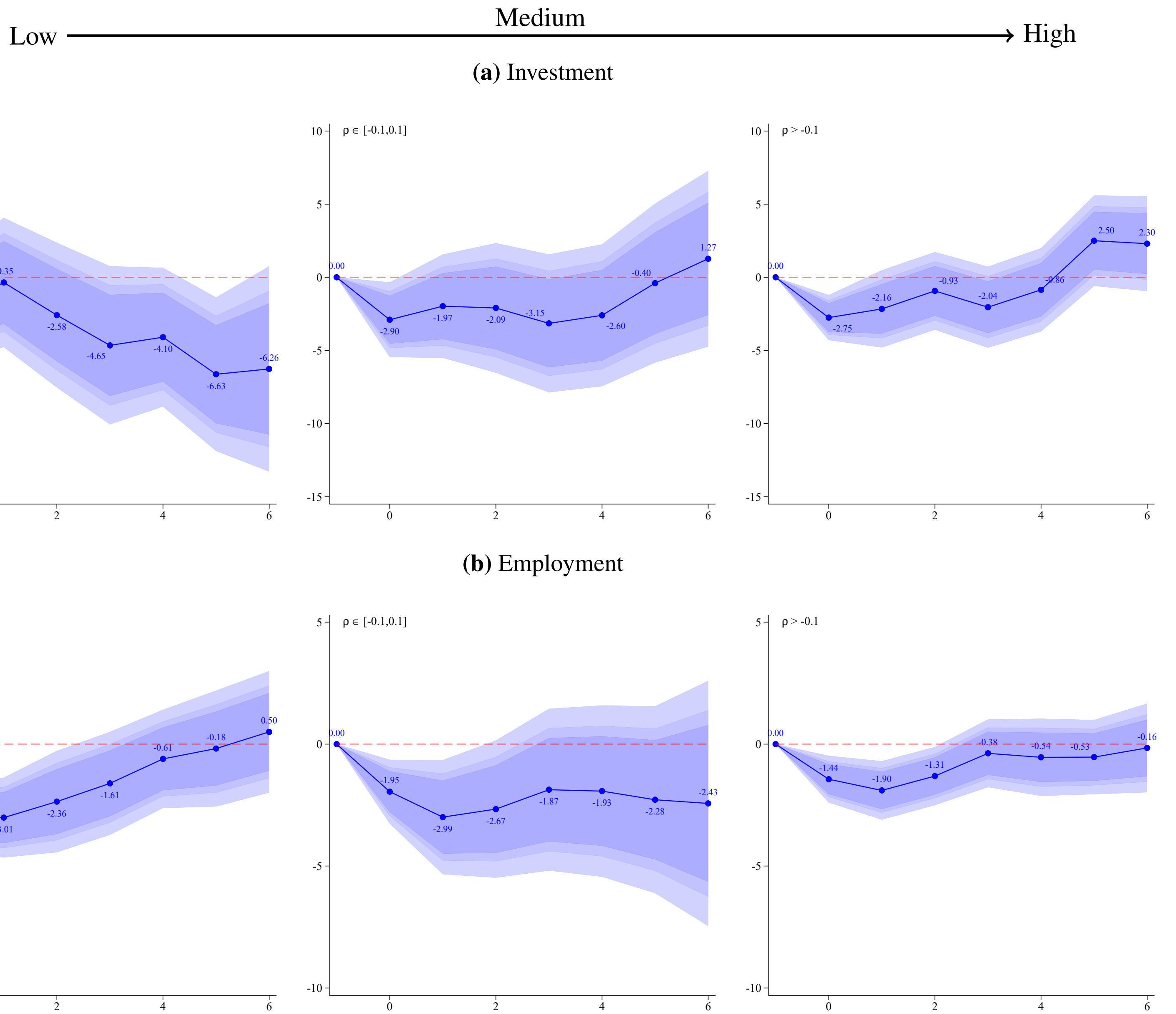
(b) Employment



NOTE: Those figures present estimates of β_2^h from estimating this equation: $\Delta G_{f,t+h} = \alpha_1^{\mathbf{h}} \mathbf{X_{f,t-1}} + \beta_1^h D_{f,t}^{IQR} + \beta_2^h (D_{f,t}^{IQR} \times \rho_f^{IQR}) + \beta_3^h \rho_f^{IQR} + \gamma_{k,t}^h + \gamma_f^h + \epsilon_{f,t+h}$. 90%, 95% and 99% error bands, computed with robust standard errors clustered at the sector-level, are displayed in shades of blue.

We repeat the same exercise for the comovement between the firm and sectoral uncertainty and show the results in Figure 6. We divide observations in three bins based on the correlation of the firm uncertainty with that of its sector. By construction, the middle bin contains comparatively less observations as it covers the $[-0.1, 0.1]$ interval. The estimates related to that bin are noisier and less useful but we report them for the sake of transparency. The key results from this exercise is that losses of firms with a positive correlation are much shorter lived for both outcomes. The effect reverts to approximately zero after two years ($h = 2$) for investment and 3 years for employment ($h = 3$). The effect on investment is increasing over time for the negative correlation bin while it takes up to four years for the employment of the firm to recover.

Figure 6: Sectoral Comovement of Demand Uncertainty

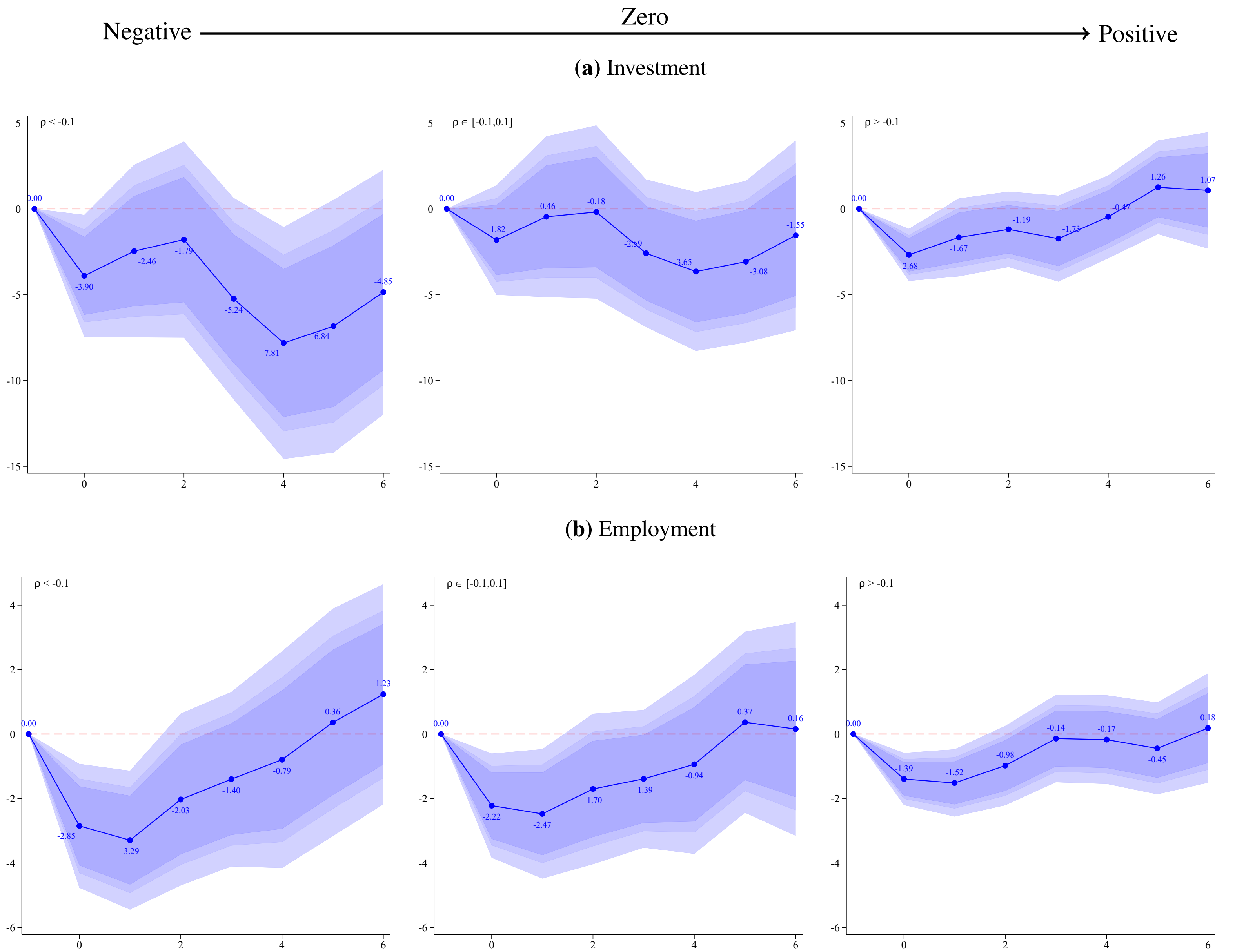


NOTE: Those figures present estimates of β_2^h from estimating this equation: $\Delta G_{f,t+h} = \alpha_1^{\mathbf{h}}\mathbf{X_{f,t-1}} + \beta_1^h D_{f,t}^{IQR} + \beta_2^h(D_{f,t}^{IQR} \times \rho_f^{IQR}) + \beta_3^h \rho_f^{IQR} + \gamma_{k,t}^h + \gamma_f^h + \epsilon_{f,t+h}$. 90%, 95% and 99% error bands, computed with robust standard errors clustered at the sector-level, are displayed in shades of blue.

Finally, we look at the impact of uncertainty conditional on the firm comovement of its sales with the sales of its sector. Once again, the same caveat regarding the number of observations in the middle bin applies. It should also be noted that the rightmost bin has more observation than the leftmost one which likely accounts for its relatively larger standard errors. We find that the contemporaneous response is l.2 p.p higher for the investment of firms with a negative correlation and 1.46 p.p. for their employment. The effect on investment is permanent within our horizon window while the effect on employment is still 1.26 p.p. stronger for $h = 3$ for the negative correlation bin.

We have explored other potential explanations to the persistence of the effect of uncertainty. Heterogeneity in terms of financial frictions, export experience, productivity or concentration fail to account for the length of uncertainty induced slowdown. However, in this section we have shown that firms in industry experiencing high uncertainty or firms that tend to be positively correlated with their sector tend to either experience a weaker initial negative impulse or recover much faster than firms that are negatively correlated. A likely explanation of this result is that the uncertainty shocks affecting exporting firms are of a varying nature. Some firms tend to experience mostly idiosyncratic shocks while other experience more aggregate shocks. This implies that the nature of the increase in uncertainty, idiosyncratic or aggregate, determine the shape of the response function of the firm.

Figure 7: Demand Uncertainty and Sectoral Comovement



NOTE: Those figures present estimates of β_2^h from estimating this equation: $\Delta G_{f,t+h} = \alpha_1^{\mathbf{h}}\mathbf{X_{f,t-1}} + \beta_1^h D_{f,t}^{IQR} + \beta_2^h(D_{f,t}^{IQR} \times \rho_f^Y) + \beta_3^h \rho_f^Y + \gamma_{k,t}^h + \gamma_f^h + \epsilon_{f,t+h}$. 90%, 95% and 99% error bands, computed with robust standard errors clustered at the sector-level, are displayed in shades of blue.

5 Robustness

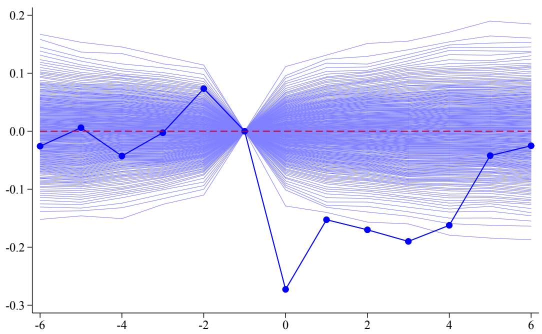
Placebo Inference

In the baseline specification, we clustered standard errors at the firm level. This provided us with standard errors that are asymptotically robust to serial auto-correlation in the error term. Here we implement Chetty et al. (2009)'s non-parametric permutation test[4] of $\beta_1^{h>0} = 0$.

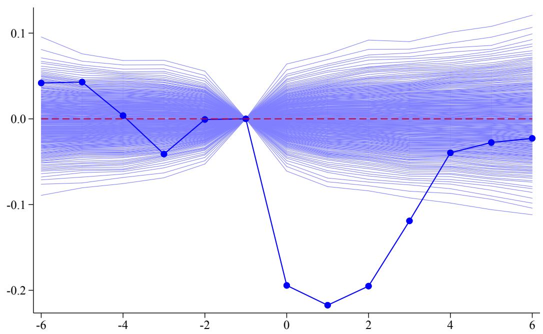
To do so, we randomly reassign the uncertainty time serie across firms and then we re-estimate the baseline regression. We repeat this process 2000 times in order to obtain an empirical distribution of the placebo coefficients $\hat{\beta}_1^{h,p}$. If demand uncertainty had no effect on firm growth, we would expect our baseline estimate to fall somewhere in the middle of the distribution of the coefficients of the placebo coefficients $\hat{\beta}_1^{h,p}$. Since that test does not rely on any parametric assumption regarding the structure of the error term, it is immune to the over-rejection of the null hypothesis highlighted by Bertrand et al. (2004).

Figure 8: Distribution of Placebo Estimates

(a) Investment



(b) Employment



NOTE: Those figures present the distribution of 2000 estimates of the coefficient $\hat{\beta}_1^{h,p}$ of Demand Uncertainty after performing a random permutation. Each light blue line represents one $200^t h$ of the distribution of the placebos. The dark blue lines corresponds to the coefficients from our baseline regressions.

We plot the distribution of the placebo coefficients in Figure 8. The figure confirms that our coefficients of interest $\beta_1^{h>0}$ (the blue connected markers) lie outside of the [p0.5,p99.5] interval (the light blue lines) of the distribution of placebo coefficients. Meanwhile, the estimates of $\beta_1^{h<0}$ fall within the bounds of the distribution of placebos, albeit narrowly so in some cases.

[4]See Malgouyres et al. (2019) for a more recent application

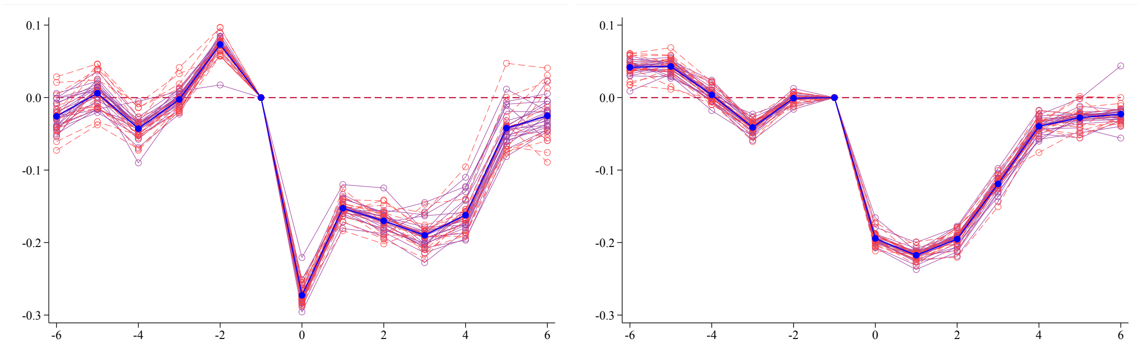
This exercise confirms that uncertainty has a negative effect on firm growth.

5.1 Sample Sensitivity

Since our sample includes events such as the Great Financial Crisis (2008 and 2009), we wish to check whether our results are robust to the omission of any particular year. We run the same baseline regressions while omitting turn by turn any year between 1996 and 2013. We plot the results in Figure 9 in red. We find results that are quantitatively and qualitatively the same as on the full sample. It shows that our specification satisfyingly accounts for the complex dynamics of our sample period. We repeat this procedure for the sectors and plot the results in purple in figure 9. This estimate is also statistically highly significant and robust to taking out any sectors (NAF 2 digit).

Figure 9: Sensitivity to sample selection

(a) Investment　　　　**(b)** Employment



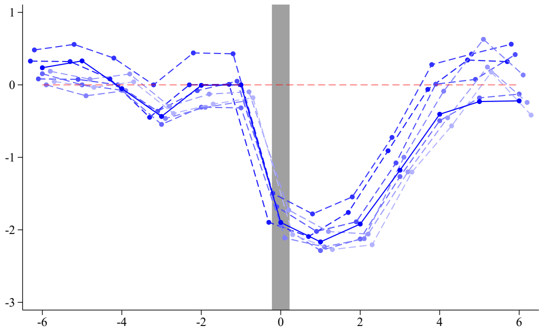
NOTE: Those figures present estimates of the coefficient β_1 of Demand Uncertainty after subtracting either a year or a sector at a time. We estimate the following equation: $\Delta G_{f,t+h} = \alpha_{\mathbf{1}}^{\mathbf{h}} \mathbf{X_{f,t-1}} + \beta_1^h D_{f,t}^{IQR} + \gamma_{k,t}^h + \gamma_f^h + \epsilon_{f,t+h}$.

5.2 Normalization Sensitivity

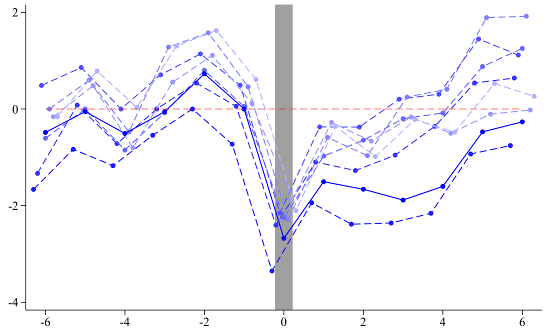
In this subsection, we show that that our main results is also robust to the choice of the period used to normalize impulse response function (See Figure 10).

Figure 10: Sensitivity to different specifications

(a) Investment



(b) Employment



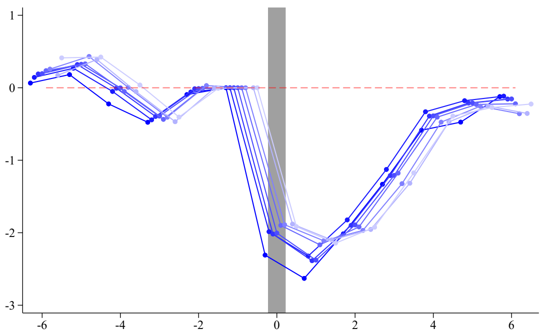
NOTE: Those figures present estimates of the coefficient β_1 of Demand Uncertainty after changing the year of reference from $t-2tot-6$ or using the average of 5 pre-shock period. We estimate the following equation: $\Delta G_{f,t+h} = \alpha_1^{\mathbf{h}} \mathbf{X_{f,t-1}} + \beta_1^h D_{f,t}^{IQR} + \gamma_{k,t}^h + \gamma_f^h + \epsilon_{f,t+h}$.

5.3 Specification Sensitivity

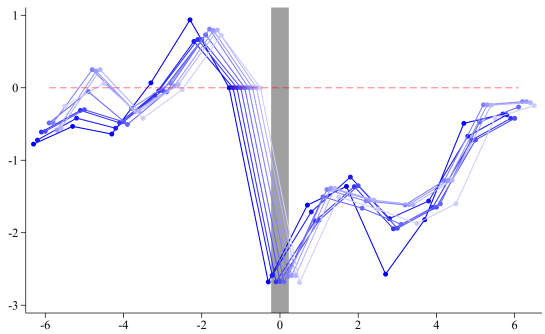
We also demonstrate that this estimate is robust to the inclusion of various observable characteristics in Figure 11. We add one by one the following variables: lagged Debt to Asset ratio, lagged cash-flow to asset ratio, an indicator variable for firms belonging to groups, lagged labor productivity, a lagged and contemporaneous measure of the raw foreign demand growth rates using the same weights as the uncertainty variable, a measure of the lagged cumulative export experience of the firm and finally a measure lagged leverage.

Figure 11: Sensitivity to different specifications

(a) Investment



(b) Employment



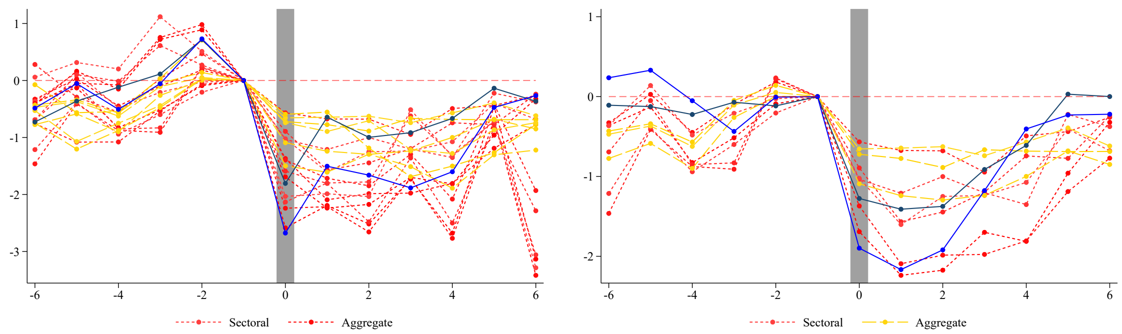
NOTE: Those figures present estimates of the coefficient β_1 of Demand Uncertainty after adding one extra control variable at a time. We estimate the following equation: $\Delta G_{f,t+h} = \alpha_1^{\mathbf{h}} \mathbf{X_{f,t-1}} + \beta_1^h D_{f,t}^{IQR} + \gamma_{k,t}^h + \gamma_f^h + \epsilon_{f,t+h}$. and add one of the following variable at a time: lagged Debt to Asset ratio, lagged cash-flow to asset ratio, an indicator variable for firms belonging to groups, lagged labor productivity, a lagged and contemporaneous measure of the raw foreign demand growth rates using the same weights as the uncertainty variable, a measure of the lagged cumulative export experience of the firm and finally a measure lagged leverage.

5.4 Weight Sensitivity

In Figure 12, we plot the distribution of the coefficients after using different weighting scheme when building the demand uncertainty variable. The lines in gold corresponds to weights computed with country level weights while red corresponds to weights computed using sector level exposure. While the baseline response function is among thus with the strongest contemporaneous effect, it is by no means an outlier. Additionally, some of the response functions using alternative weights exhibits pre-trend issues. In the case of investment, some sectoral weights present an implausible evolution at the end of the time window. The magnitude of the effect using the firm level measure based on first year weight (rather than the average of the first three years) is lower but this might reflect the partial-year effect discussed in Section 2.2.

Figure 12: Sensitivity to Various Weighting Schemes

(a) Investment **(b)** Employment



NOTE: Those figures present estimates of the coefficient β_1 of Demand Uncertainty after subtracting either a year or a sector at a time. We estimate the following equation: $\Delta G_{f,t+h} = \alpha_1^{\mathbf{h}} \mathbf{X_{f,t-1}} + \beta_1^h D_{f,t}^{IQR} + \gamma_{k,t}^h + \gamma_f^h + \epsilon_{f,t+h}$.

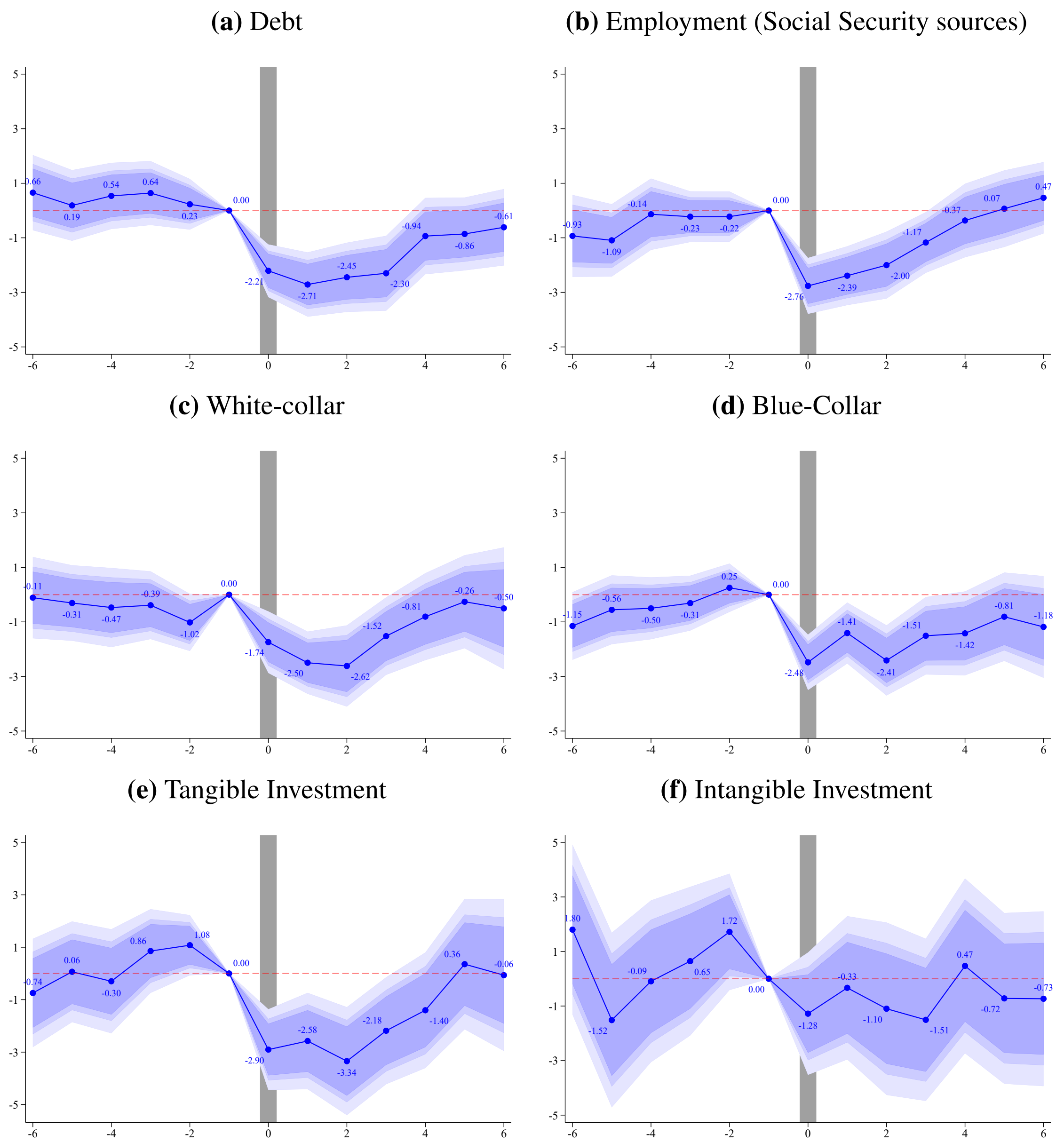
6 Conclusion

The increase in cross-border trade and financial linkages since the 1990's has led to a greater exposure of domestic agents to shocks abroad. More firms are now dependent on inherently uncertain demand conditions. In this paper, we investigate how the uncertainty around the realization of demand shocks affects the growth dynamic of French manufacturing firms between 1996 and 2013. We build a measure of demand uncertainty by computing the dispersion of estimated demand shocks from a highly dis-aggregated bilateral trade database. We then document the effect of an increase in demand uncertainty on employment and investment growth using French fiscal data. A striking result is the persistent negative effect of an increase in uncertainty. The effect lasts for up to 5 years for both investment and employment. It does not exhibit any evidence of post-shock compensation which makes those losses permanent. We find that losses are magnified for firms that tend to be negatively correlated with their sector.

While the average effect of uncertainty seems large in this study, our results suggests that aggregate losses caused by uncertainty may be rather modest. We can envision two polar scenarios. A large number of firms in a industry are affected at the same time by uncertainty. In this case, we estimate small and short lived losses for each firm. Alternatively a small number of firms is affected by uncertainty and losses will be concentrated on this limited number of firms. This implication seems particularly relevant given the current uncertainty around trade policy with the United-States and Great-Britain.

A Appendix

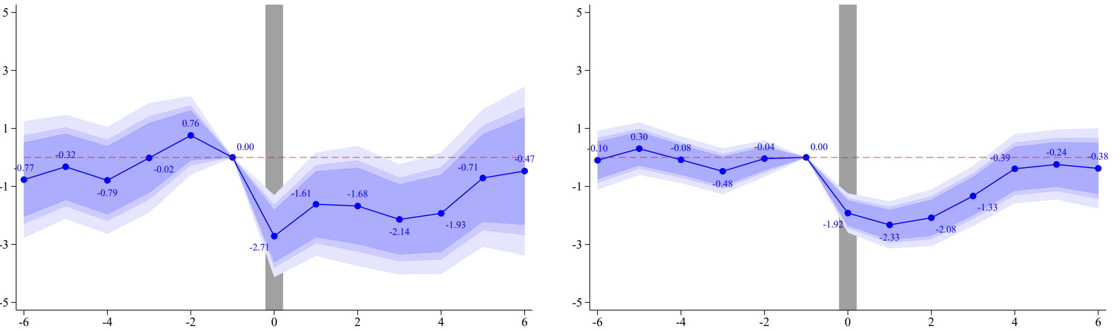
Figure A.0.13: Demand Uncertainty and Firm Growth



NOTE: This figure presents estimates of the coefficient $\beta_1^h * 100$ associated with demand uncertainty from estimating this equation: $\Delta G_{f,t+h} = \alpha_{\mathbf{1}}^{\mathbf{h}}\mathbf{X_{f,t-1}} + \beta_1^h D_{f,t}^{IQR} + \gamma_{k,t}^h + \gamma_f^h + \epsilon_{f,t+h}$. 90%, 95% and 99% error bands, computed with robust standard errors clustered at the sector-level, are displayed in shades of blue. The size of the shock is set at one standard deviation. E.g.: a one standard deviation uncertainty shock decreases investment growth by 0.45 percentage point the year of the shock.

Figure A.0.14: Standard Deviation of Demand Shocks

(a) Investment **(b)** Employment



NOTE: Those figures present estimates of the coefficient β_1 of Demand Uncertainty after subtracting either a year or a sector at a time. We estimate the following equation: $\Delta G_{f,t+h} = \alpha_{\mathbf{1}}^{\mathbf{h}}\mathbf{X_{f,t-1}} + \beta_1^h D_{f,t}^{IQR} + \gamma_{k,t}^h + \gamma_f^h + \epsilon_{f,t+h}$. Here $D_{f,t}^{IQR}$ is computed as the standard deviation of demand shocks rather than the Interquartile range.

Table A.0.3: List of Sectors

10	Manufacture of food products
11	Manufacture of beverages
12	Manufacture of tobacco products
13	Manufacture of textiles
14	Manufacture of wearing apparel
15	Manufacture of leather and related products
16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
17	Manufacture of paper and paper products
18	Printing and reproduction of recorded media
19	Manufacture of coke and refined petroleum products
20	Manufacture of chemicals and chemical products
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
22	Manufacture of rubber and plastic products
23	Manufacture of other non-metallic mineral products
24	Manufacture of basic metals
25	Manufacture of fabricated metal products, except machinery and equipment
26	Manufacture of computer, electronic and optical products
27	Manufacture of electrical equipment
28	Manufacture of machinery and equipment n.e.c.
29	Manufacture of motor vehicles, trailers and semi-trailers
30	Manufacture of other transport equipment
31	Manufacture of furniture
32	Other manufacturing

References

Aghion, P., A. Bergeaud, M. Lequien, and M. Melitz (2017). The Impact of Exports on Innovation: Theory and Evidence. Technical report, working paper.

Baker, S. R., N. Bloom, and S. J. Davis (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics 131*(4), 1593–1636.

Bardaji, J., J.-C. Bricongne, B. Campagne, and G. Gaulier (2019). Domestic and export performances of french firms. *The World Economy 42*(3), 785–817.

Barrero, J. M., N. Bloom, and I. Wright (2017). Short and long run uncertainty. Technical report, National Bureau of Economic Research.

Bernanke, B. S. (1983). Irreversibility, uncertainty, and cyclical investment. *The Quarterly Journal of Economics 98*(1), 85–106.

Bernard, A. B., E. A. Boler, R. Massari, J.-D. Reyes, and D. Taglioni (2017). Exporter dynamics and partial-year effects. *American Economic Review 107*(10), 3211–28.

Berthou, A. and E. Dhyne (2018). Exchange Rate Movements, Firm-Level Exports and Heterogeneity.

Bertrand, M., E. Duflo, and S. Mullainathan (2004). How much should we trust differences-in-differences estimates? *The Quarterly journal of economics 119*(1), 249–275.

Bloom, N. (2014). Fluctuations in uncertainty. *The Journal of Economic Perspectives 28*(2), 153–175.

Bloom, N., S. Bond, and J. Van Reenen (2007). Uncertainty and Investment Dynamics. *The review of economic studies 74*(2), 391–415.

Bussiere, M., L. Ferrara, and J. Milovich (2015). Explaining the Recent Slump in Investment: The Role of Expected Demand and Uncertainty. Technical report, Banque de France Working Paper.

Carluccio, J., C. Mazet-Sonilhac, and J.-S. Mésonnier (2018). Investment and the wacc: new micro evidence for france.

Cezar, R., T. Gigout, and F. Tripier (2017). FDI and Uncertainty: Evidence from French Multinational Firms. Technical report, Working Paper.

Chetty, R., A. Looney, and K. Kroft (2009). Salience and taxation: Theory and evidence. *American economic review 99*(4), 1145–77.

Crouzet, N., N. R. Mehrotra, et al. (2017). Small and Large Firms Over the Business Cycle. Technical report.

De Sousa, J., A.-C. Disdier, and C. Gaigné (2016). Export decision under risk.

di Giovanni, J., A. A. Levchenko, and I. Mejean (2017). Large firms and international business cycle comovement. *American Economic Review 107*(5), 598–602.

Esposito, F. (2018). Entrepreneurial Risk and Diversification through Trade.

Favara, G. and J. Imbs (2015). Credit supply and the price of housing. *American Economic Review 105*(3), 958–92.

Gala, V. and B. Julio (2016). Firm Size and Corporate Investment.

Garin, A., F. Silverio, et al. (2017). How Does Firm Performance Affect Wages? Evidence from Idiosyncratic Export Shocks. Technical report, Job Market Papers.

Gaulier, G. and S. Zignago (2010). BACI: international trade database at the product-level (the 1994-2007 version).

Gervais, A. (2018). Uncertainty, risk aversion and international trade. *Journal of International Economics 115*, 145–158.

Gilchrist, S. and C. P. Himmelberg (1995). Evidence on the role of cash flow for investment. *Journal of Monetary Economics 36*(3), 541–572.

Goldsmith-Pinkham, P., I. Sorkin, and H. Swift (2018). Bartik instruments: What, when, why, and how. Technical report, National Bureau of Economic Research.

Guiso, L. and G. Parigi (1999). Investment and demand uncertainty. *The Quarterly Journal of Economics 114*(1), 185–227.

Hassan, T. A., S. Hollander, L. van Lent, and A. Tahoun (2017). Firm-level political risk: Measurement and effects. Technical report, National Bureau of Economic Research.

Héricourt, J. and C. Nedoncelle (2016). How Multi-Destination Firms Shape the Effect of Exchange Rate Volatility on Trade: Micro Evidence and Aggregate Implications.

Hummels, D., R. Jørgensen, J. Munch, and C. Xiang (2014). The wage effects of offshoring: Evidence from danish matched worker-firm data. *American Economic Review 104*(6), 1597–1629.

Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. *American Economic Review 95*(1), 161–182.

Julio, B. and Y. Yook (2012). Political uncertainty and corporate investment cycles. *The Journal of Finance 67*(1), 45–83.

Khwaja, A. I. and A. Mian (2008). Tracing the impact of bank liquidity shocks: Evidence from an emerging market. *American Economic Review 98*(4), 1413–42.

Malgouyres, C., T. Mayer, and C. Mazet-Sonilhac (2019). Technology-induced Trade Shocks? Evidence from Broadband Expansion in France. CEPR Discussion Papers 13847, C.E.P.R. Discussion Papers.

Mayer, T., M. J. Melitz, and G. I. Ottaviano (2016). Product mix and firm productivity responses to trade competition. Technical report, National Bureau of Economic Research.

Vannoorenberghe, G. (2012). Firm-level volatility and exports. *Journal of International Economics 86*(1), 57–67.

Vannoorenberghe, G., Z. Wang, and Z. Yu (2016). Volatility and diversification of exports: Firm-level theory and evidence. *European Economic Review 89*, 216–247.

Zidar, O. (2019). Tax cuts for whom? Heterogeneous effects of income tax changes on growth and employment. *Journal of Political Economy 127*(3), 1437–1472.

Chapter 4

Exporting Ideas: Knowledge Flows from Expanding Trade in Goods

In collaboration with Philippe Aghion, Antonin Bergeaud, Matthieu Lequien & Marc Melitz

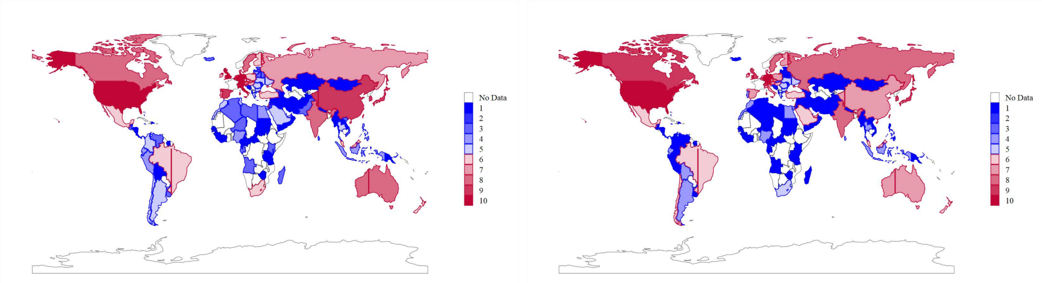
1 Introduction

Modern growth theory predicts that international trade should enhance productivity growth for several reasons. First, trade allows potential innovators to sell to a larger market; and by *increasing market size*, trade increases the size of ex post rents that accrue to successful innovators, thereby encouraging R&D investments. Second, trade *raises competition* in product markets, which in turn encourages innovation aimed at escaping competition by more advanced firms while discouraging innovation by laggard firms in the domestic economy. Third, trade *induces knowledge spillovers* which allows producers in recipient countries to catch up with the technological frontier. In previous work (see Aghion et al., 2018) we used French firm-level accounting, trade, and patent information to provide evidence on the market size and competition effects of trade expansion. In this paper, we use the same datasets to provide evidence of a knowledge spillover effect for trade expansion.

The following stylized fact motivates our analysis in this paper. In Figure 1a, we plot the long difference between the number of French exporters from 1995 to 2012 (i.e the difference between the number of French exporters in 2012 and the number in 1995) for the various geographical regions of the world. Each color corresponds to a decile in the long difference distribution across regions. Dark red corresponds to regions with the largest increase in the number of exporters from 1995 to 2012, whereas dark blue corresponds to the regions with the smallest increase in the number of exporters from 1995 to 2012. In Figure 1b, we plot the long difference between the number of citations to French patents from 1995 to 2012 for different regions worldwide; again the dark red (resp. dark red) color refers to regions lying in the highest (resp. lowest) decile in terms of long difference increases in citations. We see that those destinations experiencing the largest increase in the number of French exporters also experience the largest increase in patent citations to French innovations over the same time period. The correlation coefficient between the two long differences is equal to 77%.

Figure 1: Evolution of Trade and Innovation Linkages

(a) Number of French Exporters (b) Citations



Notes: Evolution in the number of French exporters in each country (left-hand side panel) and the number of citations received from each country (right-hand side panel) between 1995 and 2012. Colors correspond to different deciles in the corresponding quantity.

We begin with a comprehensive set of patents belonging to French exporters over the 1995-2012 period. For every year and potential export destination, we construct a citation count for each exporters' patents. These citations come from new patents introduced in that year by firms operating in the destination country. We then investigate how a French firm's citation count in a destination changes whenever that firm starts exporting to that destination. Increases in a new exporter's citations represent new patents recorded in that destination subsequent to the exporter's entry into the destination. Those patents citing the French exporter represent a measure of its technological influence in that destination. We use the timing of the exporter's entry into a market and its citations in that market to infer a causal relationship between the two.

We show that exporting to a new foreign market increases the flow of citations received by the exporter from that market. The underlying idea is that entry into that new market raises the visibility of the exporter's technology to domestic firms in the market. Those domestic firms can then more easily generate further innovations that build on that technology, conditional on the host country's degree of absorptive capacity (Cohen and Levinthal, 1989).

Our identification strategy to deal with potential selection effects (in particular for the fact that exporting firms have better technologies or technologies that are better suited to the destination country) is adapted from Watzinger et al. (2017, 2018), who study the knowledge spillovers induced by professor transfers across universities. We use a difference-in-difference strategy to analyze the response of patent citations to a French firm's export market entry in a particular year: We compare this firm's citations with citations for other French firms with an *ex-ante* similar probability of entry who did not enter that market in that particular year.

We thus start by estimating the probability for each firm of entering an export destination for the first time in any given year. We then group all the French firms that belong to the same probability percentile into an "iso-probability bin" for that destination-year. Within each bin, there are firms that enter the foreign market early, or late, or never; and there are firms that exit that foreign market early, late or never. This first-stage analysis allows us to construct an "entry" variable which is immune to potential selection issues. In a second stage, we examine the impact of entry on the knowledge flows between the entering French exporter and the destination country – *relative* to its control group. We measure the knowledge flow using the number of new priority patents in the destination country citing the French firm's patents.

Following this event-study design, we regress the citation outcome on a set of dummy variables that indicate whether or not the firm entered the foreign market for the first time. We allow the effect to vary across time by including one dummy per year relative to the entry year. We also add an iso-probability bin fixed effect. The coefficients for this regression are thus estimated within a bin of firm-destination-year triplets with very similar entry probability: this is our control group.

We first implement this specification in a dynamic setting with a full set of leads and lags dummies to test for pre-entry effects. Once we confirm the absence of an anticipatory effect, we run the model in a semi-dynamic setting to compute the treatment/causal effect of entry on patent citation.

Our first main finding is that this impact of entry on citations (and hence knowledge flows in the destination) is positive and significant starting 3 years after export market entry, and peaking after 5 years.[1] Quantitatively, we find that export market entry induces an 18% increase in the exporter's mean citation rate. We also find that export market entry leads to a 1 pp increase in the probability of receiving citations for exporters with no citations.

Our second finding is that those positive effects are significant only at the top of the productivity distribution for French exporters (it is concentrated among the most productive exporters). This is consistent with the view that the patents owned by more productive firms embody more/better knowledge that spills over to other firms and inventors.

Our third finding regards the characteristics of destinations that receive these knowledge spillovers. We find that a destination's level of development (as measured by GDP per capita) strongly influences those spillovers. We find that the spillover intensity is hump-shaped with a peak around 55-60 percentile of the GDP per capita distribution across destinations. The spillover intensity steadily decreases with development for richer countries beyond that peak – but remains positive. We also find a negative and significant spillover for the poorest set of destinations. This is consistent with the view that firms in those destinations have much lower "absorptive capacity" to use the knowledge spillover from the new French exporters, and mainly suffer from the increased competition effect generated by those French firms. Development then enhances a destination's ability to absorb - and build upon - the technology of the French exporters. At the other end, highly developed destinations may have already discovered the technologies that would allow them to make use of the French firm's technology.

Overall, our results vindicate Cohen and Levinthal (1989)'s view stated in the following quote: "*Economists conventionally think of R&D as generating one product: new information. We suggest that R&D not only generates new information, but also enhances the firm's ability to assimilate and exploit existing information. [...] we show that, contrary to*

[1] This timing lag is consistent with the time needed post-entry for new research to generate new priority patents

the traditional result, intra-industry spillovers may encourage equilibrium industry R&D investment." (Cohen and Levinthal, 1989, p.569). Our analysis relates to several other strands of literature. There is first the literature on spillovers and trade, starting with Coe and Helpman (1995a), who show that a country's TFP is positively correlated not only with domestic R&D but also with foreign R&D and to an extent which increases with the country's degree of openness to foreign trade.[2] We contribute to this literature by using firm-level data and patent citation data to identify a causal effect of export on the innovative activity in the destination country.

Second, our paper relates to the recent literature on trade and innovation, including papers on both, imports and innovation (see Bloom et al., 2016; Autor et al., 2016; Bombardini et al., 2017) and on exports and innovation (see Lileeva and Trefler, 2010; Aghion et al., 2018). Overall, this literature concentrates on the competition and market size effects of trade. We contribute to that literature by looking at the technological spillover effects of trade, and more precisely at how exporting to a destination country affects the exporting firm's patent citations by firms in that destination country.

Third is the literature on academia, scientists and citations. Thus Azoulay et al. (2010) and more recently Jaravel et al. (2018) analyze the impact of an inventor's death on the subsequent innovation and income patterns of the inventor's surviving coauthors. Waldinger (2011) analyzes the impact of the dismissal of Jewish scientists's by the Nazi government in Germany in the '30s. And Watzinger et al. (2017, 2018) analyze the impact of the mobility of scientists across German universities on local citations to their work. We contribute to this and the broader literature on knowledge spillovers and absorptive capacity by looking at how trade interacts with knowledge spillovers and absorptive capacity.[3]

The remaining part of the paper is organized as follows. Section 2 briefly presents the data and details our empirical strategy and section 3 shows our baseline results. We conduct

[2] See also Keller and Yeaple, 2009, Coe et al., 2009, and Keller and Yeaple, 2009.
[3] See Aghion and Jaravel (2015) for more detailed references to that literature.

further robustness tests in section 4. Section 5 concludes.

2 Data and Methodology

2.1 Data

We build a database covering all French firms and linking export, production and innovation/citation data from 1994 to 2012. Our database builds on three separate sources. First, detailed customs data provide French exports by product and country of destination for each French firm over 1993-2012. Every firm must report its exports by destination country and by very detailed product (with a classification of 10,000 different products consistent with 8-digit HS codes). From this database, we extract the date of first entry into a foreign market for each firm. Our second data source is the INSEE-DGFiP administrative fiscal dataset (FICUS-FARE), which provides extensive production and financial information for all firms operating in France. This data is drawn from compulsory reporting to fiscal authorities in France, supplemented by further census data collected by INSEE.

Our third data source is the Spring 2016 PATSTAT dataset from the European Patent Office. This contains detailed information on all patent applications from most of the patent offices around the world. We use information on the network of patent linkages via citations. Although each French firm has a unique identifying number (Siren) across all French databases, patent offices identify firms using only their name. The recording of the name is sometimes inconsistent from one patent to another, and may also contain typos. Various algorithms have been developed to harmonize assignees' names (for example this is the case of the OECD's Harmonized Assignee Name database) but none of those have been applied specifically to French firms. One notable exception is the rigorous matching algorithm developed by Lequien et al. (2019) to link each patent application with the Siren numbers of the corresponding French firms; for all firms with more than ten employees. Based on supervised learning, this new method provides significant performance improvements relative to previous methods used in the empirical patent literature: its recall rate (i.e. the share of all the true matches that are accurate) is 86.1% and its precision rate (i.e. the share of the identified matches that are accurate) is 97.0%. This is the matching procedure we use for our empirical analysis in this paper.

We seek to measure the knowledge spillovers from French exporters to firms located in the exporters' sales destinations. Towards this goal, we count the total number of priority patents filed in each destination and year (1995-2012) that cite any patent filed by a French exporter. We restrict our count to *priority* patents as those indicate genuine innovations: Non-priority patents, by and large, reflect a geographical expansion for the protection for a priority patent.

Table 1 summarizes this data. Over our sample years, 5339 French firms have filed patent applications that have been cited at least once in a foreign destination. Across those 137 destinations reached by French exporters, 26552 priority patents have been filed citing those French firms. Of those 26552 linkages, 19691 have been "treated" in the sense that the cited French firm has entered the corresponding export destination during our sample years.

Table 1: Descriptive Statistics

Level	N
Years	18 (1995-2012)
Countries	137
Firms	5,339
Patent	114,993
Links (firms * country)	26,552
↪ Ever treated	19,691

Notes: Links to pairs of firm-country (f,j) where the stock of patents of f has received at least 1 citation from j over the observed period.

2.2 Empirical methodology

We want to estimate how a French firm's entry into a new export market affects the flow of new patents (in that destination) citing that firm's patents. One immediate concern is that the correlation between entry and the subsequent increase in citations may partly reflect the fact that better performing firms (with patents that are more likely to be cited) have a higher probability of entering new export markets. To deal with this selection problem, we follow Watzinger et al. (2017, 2018), who study the knowledge spillovers induced by professor transfers across universities. Those authors use administrative data from German universities. Every year a university in Germany creates a list of professors eligible for transfers. The probability of transfer within that list is as good as random. The authors then measure the effect of mobility within a list of eligible professors on the Patent-to-Article and Article-to-Article citation counts.

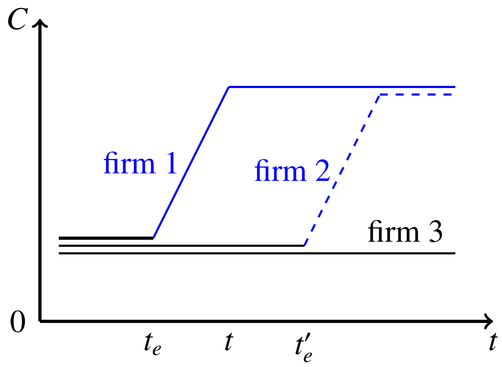
Similarly, we construct a control group of French firms for every French exporter observed to enter a new foreign market in a given year. Firms in this control group have a similar (same percentile) probability of entering that destination in that given year. All of our subsequent regressions on patent/citations flows are then reported *within* this control group (a "diff-in-diff" approach). We thus start by estimating the probability that each French firm enters an export destination for the first time in each year. We then partition all those firms (by destination-year) into bins according to their predicted entry percentile. Within each bin, there are firms that enter the foreign market early, or late, or never; and there are firms that exit that foreign market early, late or never. This first-stage analysis allows us to control for the selection endogeneity by always comparing an entrant (exporter to a new destination) within its control group in our second stage.

In that second stage, we measure the impact of export entry on the knowledge flows between the entering firm and new priority patents in the destination (citing the exporter's prior patents). As is customary for an event-study, we regress this new patent/citation outcome on a set of dummy variables capturing the time lag (measured in years) relative to the exporter's entry into a destination. We control for export entry selection by adding the iso-probability bin fixed effect we previously described. Thus, our results are estimated within a bin of firm-destination-year triplets with very similar probabilities of export market entry. In the remaining part of this section we provide further details on this empirical methodology.

2.2.1 First stage regression

As explained above, our first stage seeks to generate differences in the timing of entry that is *as good as random* within the iso-probability group. In Figure 2 we depict three firms with the same probability of entering a new foreign market in year t. Firm 1 enters this destination at date $t_e < t$. Firm 2 enters that same destination at date $t'_e > t$, while firm 3 never exports to that destination. Consider "treated" firms that enter this destination in year t. We estimate the average effect of entry in that year relative to those 3 firms who did not enter that destination in year t, yet have a very similar probability of having done so.

Figure 2: Exploiting random difference in timing within iso-probability bins



In particular, this grouping will control for two other important types of technological spillovers originating from French firms and their patents. One type does not involve any trade linkages and depends only on the fact that a French firm's technology can be observed via its patent applications (a purely "technological" link). In Figure 2, citations of firm 2's and firm 3's patents in that destination in year t must come via this link (since those firms have not exported to the destination as of year t). The other type of spillover involves a current ongoing trade relationship in year t. Citations of firm 1's patents may fall in this category as this firm is currently exporting in that destination in year t. We use the word "may" as we also measure a potential delayed impact of firm 1's entry in $t_e < t$ in year t. Our regression method allows us to separate out the impact of entry relative to the impact of a current ongoing trade relationship by using the timing of market entry and new citations (observed in new priority patents from that destination).

For each firm-destination-year, we estimate a probability of initial market entry. We estimate this first stage regression as a logit specification:

$$\Pr(ENTRY_{f,j,t}) = \alpha_G GRAVITY_{j,t} + \alpha_F FIRM_{f,t} + \varepsilon_{f,j,t}, \tag{1}$$

where: (i) $ENTRY_{f,j,t}$ is a dummy variable equal to one if firm f enters destination j at date t, and is equal to zero otherwise; (ii) $GRAVITY_{j,t}$ is the usual vector of gravity variables

Table 2: Probability of First Entry

	$Pr(ENTRY_{f,j,t})$
Ln $GDP_{j,t}$	0.424***
	(262.50)
Ln $GDPpc._{j,t}$	-0.014***
	(-9.88)
Ln $Distance_{j,t}$	-0.132***
	(-66.61)
Ln $Employment_{f,t}$	0.630***
	(541.3)
Ln $Productivity_{f,t}$	0.217***
	(114.33)
Constant	-4.644***
	(-238.57)
Destinations-Years	452898

z statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

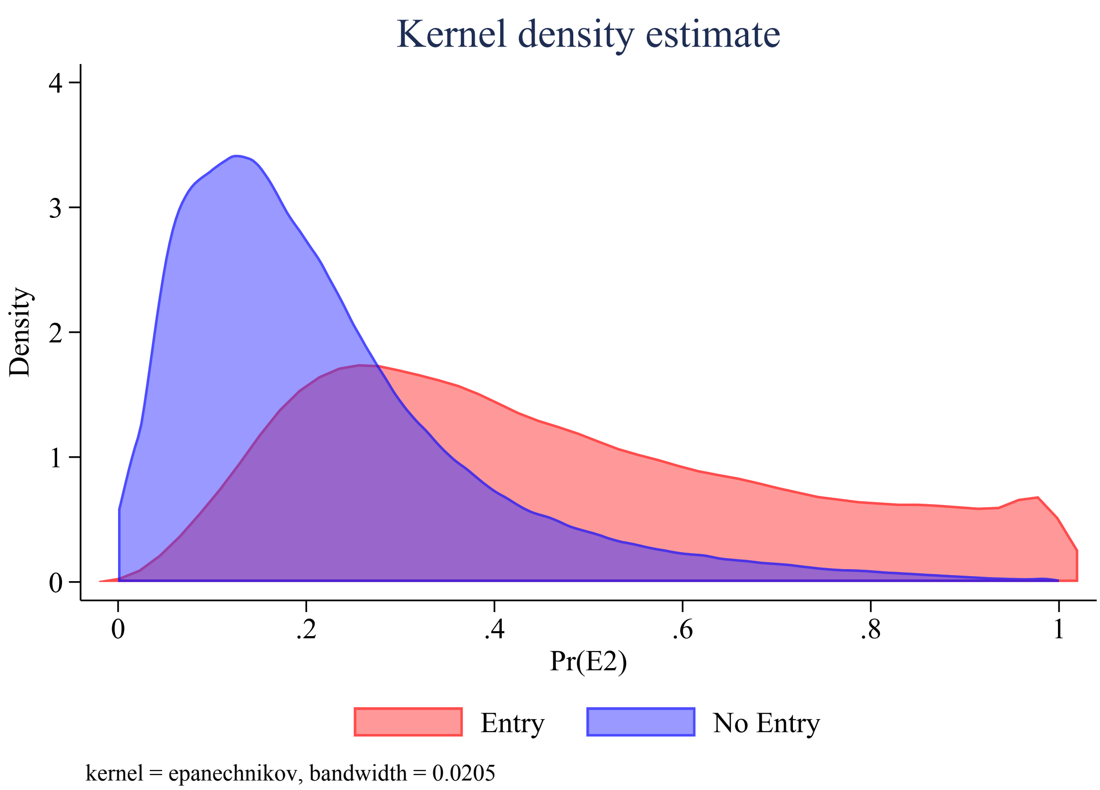
measuring the importance of destination country j for France at date t (this includes the geographical distance between France and country j, GDP and per capita GDP of country j at date t); (iii) $FIRM_{f,t}$ includes firm-year characteristics (size, labor productivity measured as value-added per employee).

Table 2 shows the results from this first-stage regression. These results match the standard results we find in the gravity literature. In particular, French firms are less likely to enter destinations that are farther away from France, and more likely to enter bigger foreign markets. Additionally, bigger and more productive French firms are more likely to enter any given foreign market.

We present the distribution of the estimated propensity score for firms that enter and firms that stay out in Figure 3. It illustrates that there is enough overlap between the two distributions to allow the construction of equally likely bins.

We assign French firms to the same bin if their probability to enter country j at date t belongs to the same percentile of the distribution of all the probabilities to enter destination j at date t for all French firms. As a robustness test, we also run specifications with larger-

Figure 3: Distribution of Propensity Score for Entry and non Entry



Notes: This figure shows the density function of the estimated propensity score for firms that enter and firms that do not enter.

sized bins.

2.2.2 Second stage regression

In our second stage, we estimate how the citations in destination j and year t respond to a French firm f's export market entry into j in year t_e. We estimate the following regression via OLS at the patent-level $p(f)$ (instead of the firm-level f) so that we can separately control for each patent's characteristics such as its prior citations and its filing year $t_{p(f)}$:

$$Y_{p(f),j,t} = \sum_{\substack{k=k_{min} \\ k\neq -1}}^{k_{max}} \beta_k \times ENTRY_{f,j,t-k} + \gamma_{bin} + \delta \times X_{p(f),t_e-1} + \gamma_{t_e} + \gamma_{t_{p(f)}} \times \gamma_z + \gamma_t \times \gamma_z + \varepsilon_{p(f),j,t}, \quad (2)$$

where $Y_{p(f),j,t}$ is the number of priority patents by applicants in destination country j citing patent $p(f)$ at date t; $ENTRY_{f,j,t-k}$ is a dummy equal to one if French firm f enters destination j for the first time at date $t_e = t - k$; and γ_{bin} is the *iso-probability bin* fixed effect (percentile for the firm-destination-year triplet).

We also control for the number of citations the patent has received worldwide prior to entry $X_{p(f),t_e-1} = \sum_{t=-\infty}^{t_e-1} Y_{p,f,World,t}$. We also control for the global cycle of innovation within each technological field when the French and foreign (j) patent were filed by introducing the dummies $\gamma_{t_{p(f)}} \times \gamma_z$ and $\gamma_t \times \gamma_z$, where γ_z is a two-digit technology class fixed effect. We also add a dummy for the entry date γ_{t_e}. Lastly, we cluster the standard errors at the link-level: by firm-country (f, j) pair.

We first run this specification using a fully dynamic set up: that is, we include dummies for a pre-entry effect ($k_{min} \leq -2$). Once we confirm the absence of anticipatory effects, we run the model using a semi-dynamic specification to compute the treatment effect, with $k_{min} = 0$.

We then repeat the same regression using different dependent variables in addition to the number of citations C: (i) $\log(1 + C)$; (ii) $\mathcal{H}(C)$, a hyperbolic function[4] which gives more

[4] $\mathcal{H}$ is the arsinh function: $\mathcal{H}(C) = \frac{1}{2}\log\left(C + \sqrt{1 + C^2}\right)$

weight to the extensive margin; (iii) a dummy variable equal to one if $C > 0$, and to zero otherwise; this is simply a linear probability model that allows us to evaluate an extensive margin effect of export on patent citation (a transition from no citations to positive citations); (iv) the log difference of the cumulative stock of citations. Since we can only compute this variable for patents that receive at least 1 citation, this specification conditions on the set of patents that are cited in the destination.

2.2.3 Introducing heterogeneity

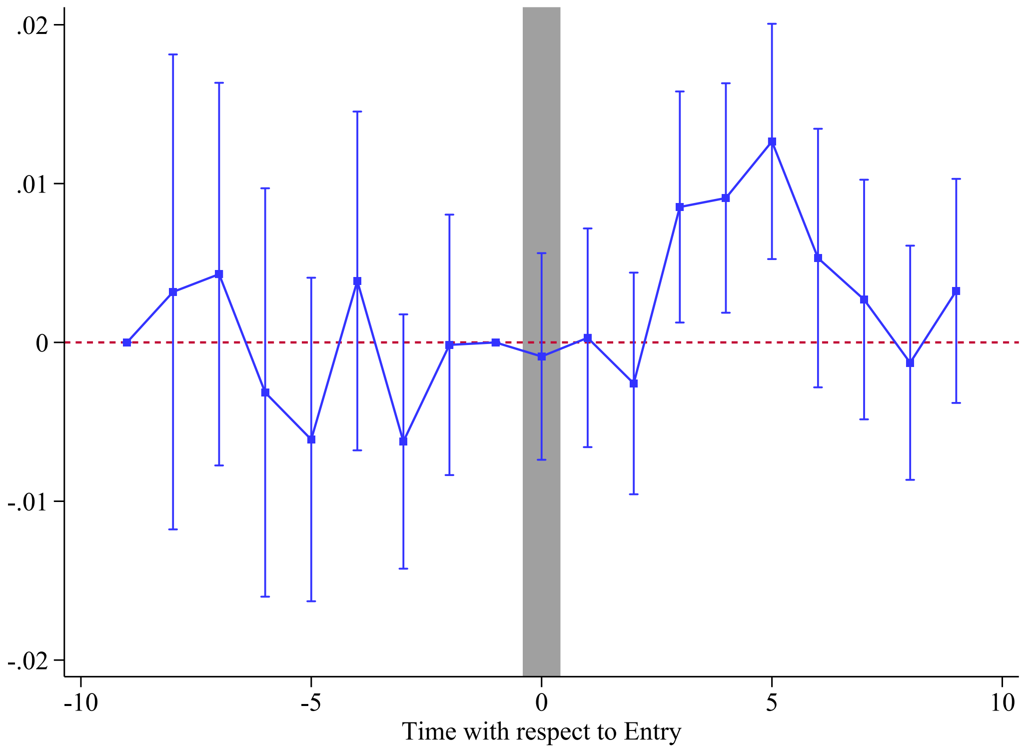
To conclude our second-stage analysis, we estimate variants of the specification above. In particular: (i) we first use a static version of the treatment variable with a unique entry dummy equal to 0 before entry, to 1 thereafter, and then to 0 again when/if the firm exits; (ii) we introduce local effects with a kernel re-weighting scheme across the various percentiles in the variable that generates the heterogeneity. To do so, we follow the methodology detailed by Hainmueller et al., 2016. This kernel approach allows us to flexibly estimate the functional form of the marginal effect of entry on patent citations across the distribution of the heterogeneous variable. We focus attention on two main sources of heterogeneity: (a) the heterogeneity in French firms' productivity; and (b) the heterogeneity in the levels of development across destination countries.

3 Results

3.1 Baseline results

Figure 4 graphically depicts all the estimated leads and lags coefficients for entry (the main coefficients of interest $\hat{\beta}_k$), along with their 95% confidence intervals, for our fully dynamic specification with pre-entry periods (with the dependent variable measured as the flow of citations C). We first verify that there is no difference between the treated group and the control group prior to entry: the regression points for the leads fluctuate around zero and are not significant. But entering into a market leads to a marked and significant increase in citations after 3 years – lasting for 3 years (3 to 5 years post-entry). This effect progressively dies out thereafter.

Figure 4: Main Specification: Priority Citations Count

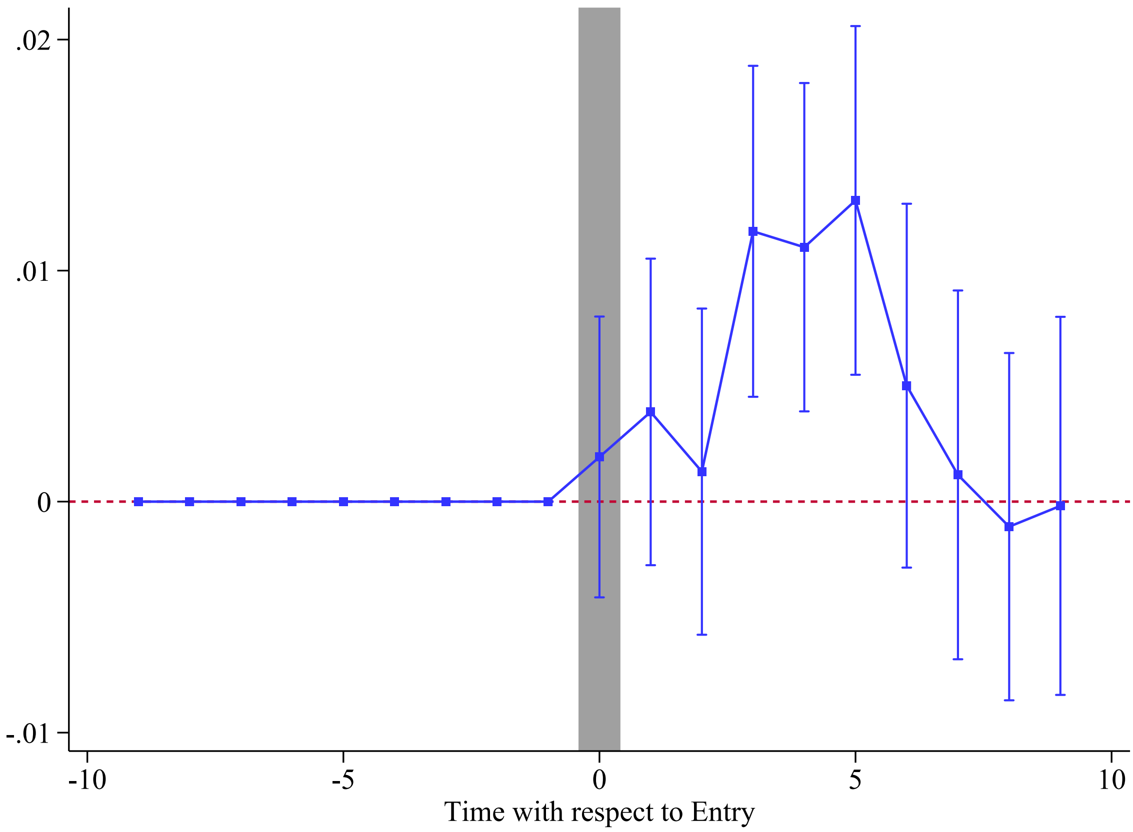


Notes: This figure shows the coefficients β_k from the estimation of our baseline Equation 2. 95% confidence interval are presented. Standard errors are clustered at the link level.

Figure 5 repeats the same exercise as Figure 4, but uses a semi-dynamic specification where we omit the pre-trend dummies to gain additional years of observations. This figure shows similar post-entry effects to those in the fully dynamic specification (both in magnitudes and in precision): entry increases received citations 3 to 5 years after entry, and has no significant impact at shorter or longer horizons.

Quantitatively, firms entering into a destination receive an additional 0.011-0.013 citations for their patents from that destination 3 to 5 years after entry, compared to similar firms that had not entered that destination at that time. This corresponds to a 16-18% increase

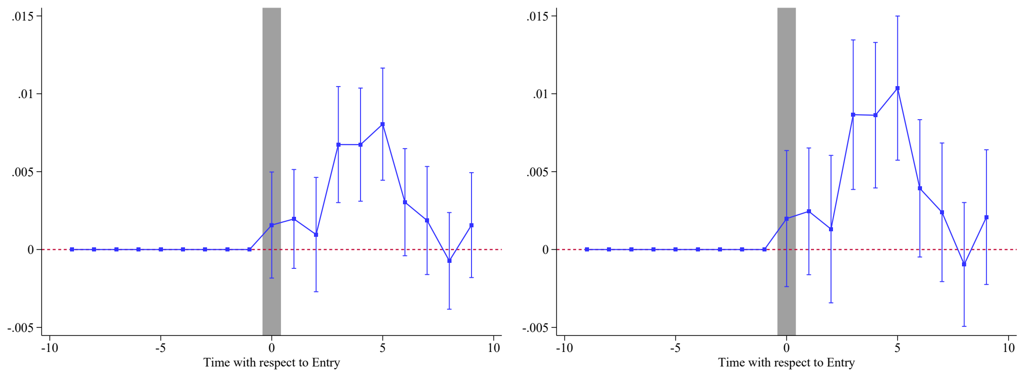
Figure 5: Y = Priority Citations Count



Notes: This figure shows the estimated $\hat{\beta}$ coefficients from the estimation of our baseline Equation 2 in its semi-dynamic specification. The dependant variable is the priority citations count. 95% confidence interval are presented. Standard errors are clustered at the link level.

Figure 6: Main Specification: alternative LHS variables

(a) Y = log(1+C) (b) Y = arsinh(C)



Notes: This figure shows the estimated $\hat{\beta}$ coefficients from the estimation of our baseline Equation 2. The dependant variable is $\log(1 + C)$ in the left panel, and arsinh(C) in the right panel. 95% confidence interval are presented. Standard errors are clustered at the link level.

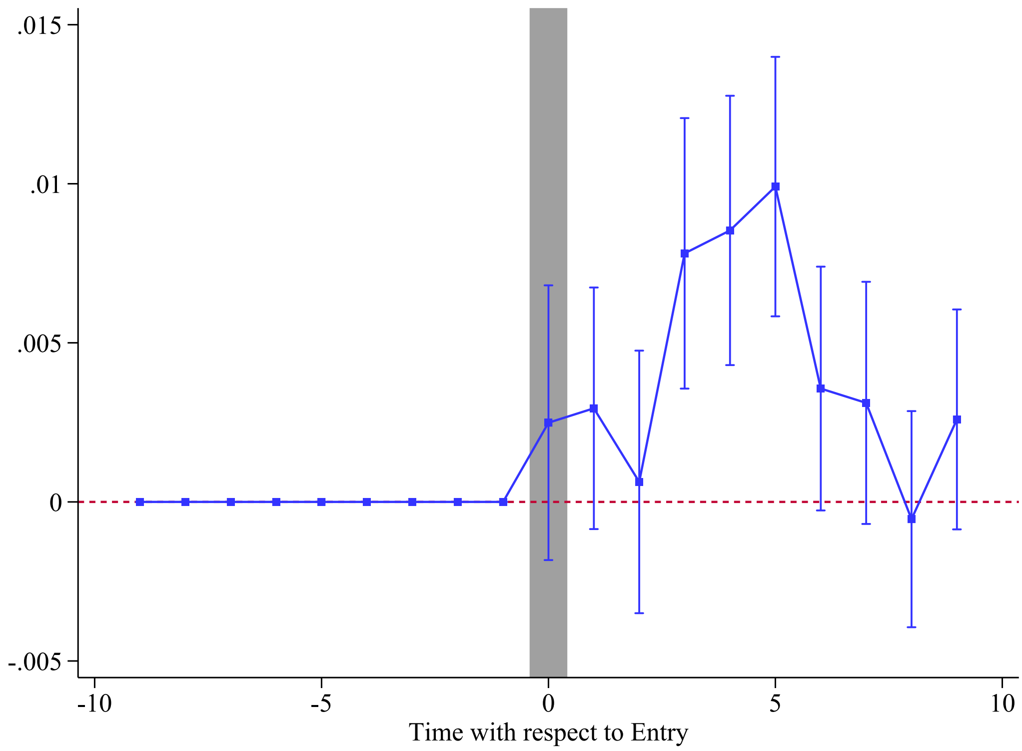
from the mean citation rate in our sample.

In order to assess the magnitude of the full treatment effect, we compute the sum of coefficients and find a total coefficient of 0.0497. Over this 9 year time window after entry, a firm receives an average of 0.51 citations whereas a firm that does not export to that destination receives an average of 0.46 citations. This corresponds to a 13.3% increase in citations from the export destination country.

In the following two figures, we explore the impact of changing the functional form for the number of citations C dependent variable – sticking with our semi-dynamic specification. In Figure 6a the dependent variable is $\ln(1 + C)$, whereas in Figure 6b the dependent variable is $\mathcal{H}[C]$. These figures confirm that the pattern from out baseline Figure 5 is not particularly sensitive to changes in the functional form of the dependent variable.

We now decompose the overall response of citations into an extensive margin component – a binary transition from no citations to positive citations – and an intensive margin component – an increase in citations conditional on a positive number of citations. Figure 7 shows the result from the binary response regression. As we previously discussed, the results can be interpreted as a linear probability model yielding the probability that an entrant is cited in the export destination. We see that this dynamic pattern is very similar to our baseline regression, with a significant increase in the citation probability 3 to 5 years after entry. The probability of being cited increases with entry 3 to 5 years after entry. Entry increases the probability of a citation by almost 1 percentage point 3 to 5 years after entry. This implies that an entering firm is 36% more likely to obtain a citation relative to a firm that does not enter in that same year (the probability of receiving a citation for such a firm is around 4%).

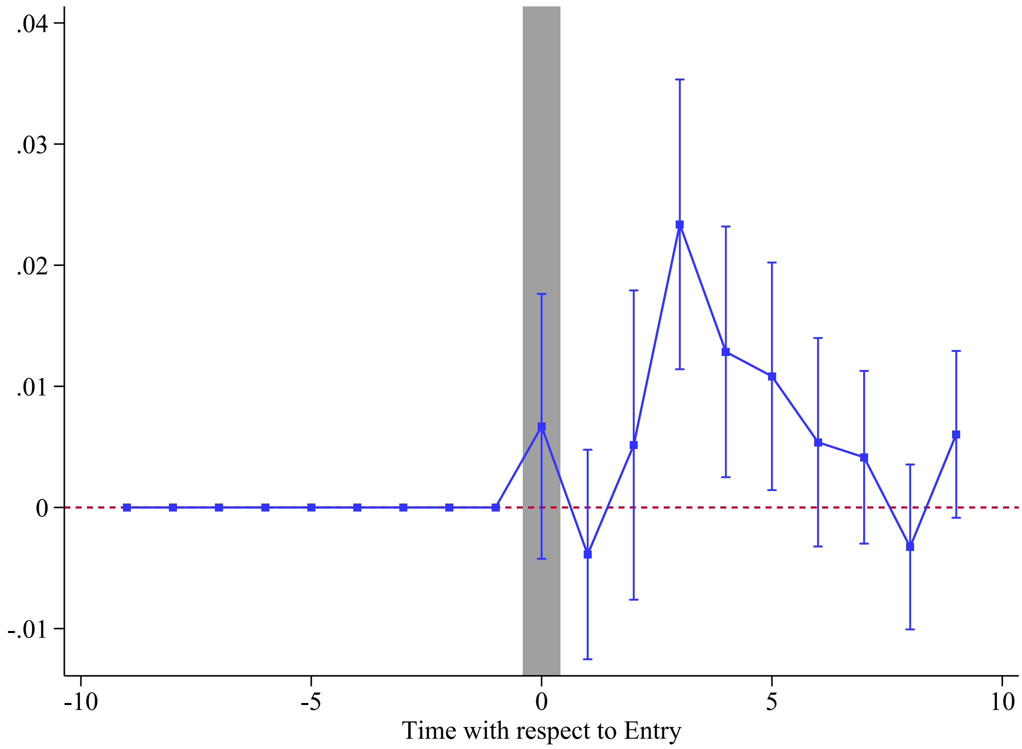
Figure 7: $Y = \{0, 1\}$



Notes: This figure shows the estimated $\hat{\beta}$ coefficients from the estimation of our baseline Equation 2. The dependant variable is the status of the technological link between the firm's applicants and the foreign country's applicants. 95% confidence interval are presented. Standard errors are clustered at the link level.

In Figure 8 we condition on the subset of patents receiving at least 1 citation and measure the increase in citations with the log difference in the stock of citations. This figure shows a pattern that is slightly different from the one in the baseline Figure 5. Once again, the effect becomes significant 3 years after entry; but it reaches its maximum that same year (with a 2.23 percentage point increase in citation from the destination country) and then decays thereafter. The effect is no longer significant beyond year 5. The sum of coefficients amounts to an aggregate coefficient of 0.0689, which yields an average extra 0.7 percentage point growth rate in citations per year from the destination country over the whole time window – compared to firms that did not enter the destination country. Overall, citations to a patent of a firm that entered will have grown by 46 percent versus 36 percent for the patent of a firm that did not enter the destination country.

Figure 8: Y = Δlog Cumulative Citation Stock



Notes: This figure shows the estimated $\hat{\beta}$ coefficients from the estimation of our baseline Equation 2. The dependant variable is Δlog Cumulative Citation Stock. 95% confidence interval are presented. Standard errors are clustered at the link level.

3.2 Heterogeneous effects

In this subsection, we investigate how the impact of entry on citations varies with both the exporting firm's productivity (an indication of the technology embodied in the patents), and the level of development of the destination country (which we use as a proxy for the country's degree of absorptive capacity). As we already mentioned, we measure these heterogeneous responses by moving to a static version of the treatment variable with a unique entry dummy equal to 0 before entry, to 1 thereafter, and then to 0 again when/if the firm exits. Moreover, we use a kernel re-weighting scheme across the various percentiles in the variable with heterogeneous effects. The kernel approach allows us to flexibly estimate the functional form of the marginal effect of entry on patent citation across the percentiles in the heterogeneity variable. Each dot in the figure corresponds to the effect on citations estimated at a given percentile of the heterogeneous response variable (with Gaussian weights and a bandwidth of 15 percentiles).

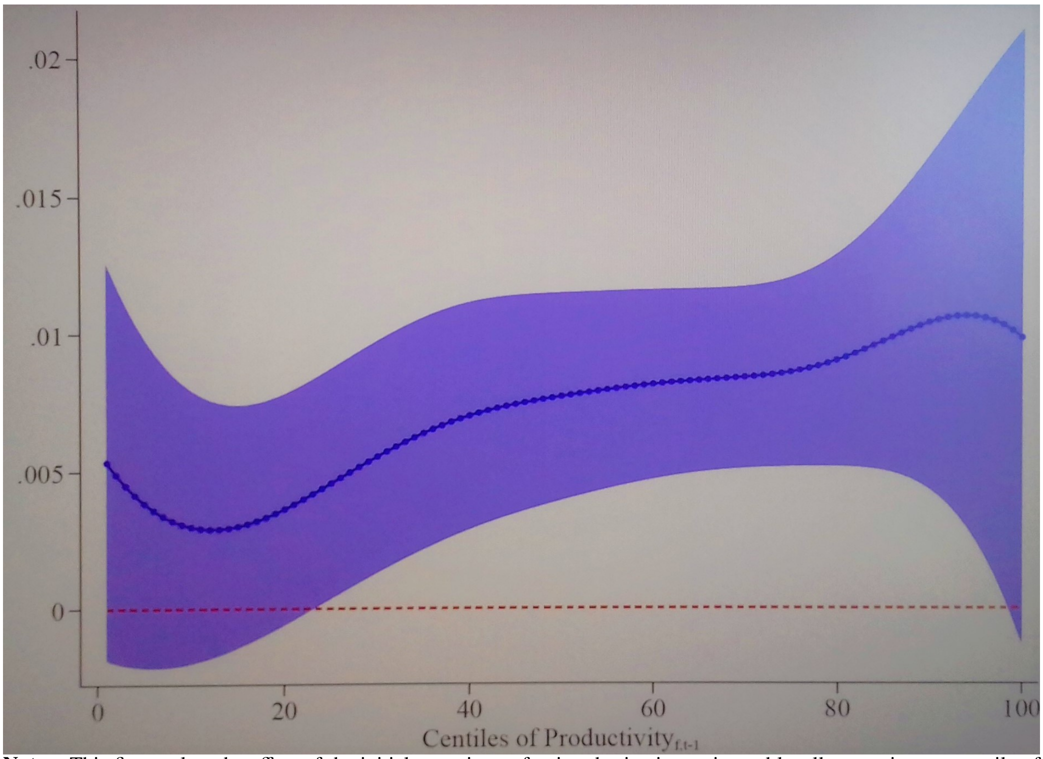
3.2.1 Impact of the exporting firm's productivity

A more productive firm is expected to generate patents that embodies better/more valuable technologies. Those patents are presumably more likely to induce follow-up innovations by other firms, and should be reflected in additional citations whenever those innovations lead to new patents. To test this prediction, we adapt the baseline second stage regression to allow for varying β coefficients across percentiles in the distribution of French firm's productivity (at date $t-1$) at the entry stage. Productivity is measured by the firm's value added per employee. In Figure 9, each dot corresponds to the effect of the initial entry into a foreign market estimated locally at a given percentile of the ex-ante productivity distribution. The blue band corresponds to the 90% confidence interval. We see that the effect of entry on citation is linearly increasing in productivity and that spillovers becomes significantly different from zero above the $20th$ percentile.

3.2.2 Impact of a destination's development level

The transfer of knowledge from a French exporter to firms in the export destination is likely to depend upon the destination's technological development relative to the French exporter. If firms in the destination country lag far behind the French firm, then presumably these firms are not adequately equipped to build on the French firm's innovation, and therefore the French firm's entry should have limited impact on innovation in the destination country. The French firm might even deter such innovation in the destination country due to the

Figure 9: Productivity and Spillovers



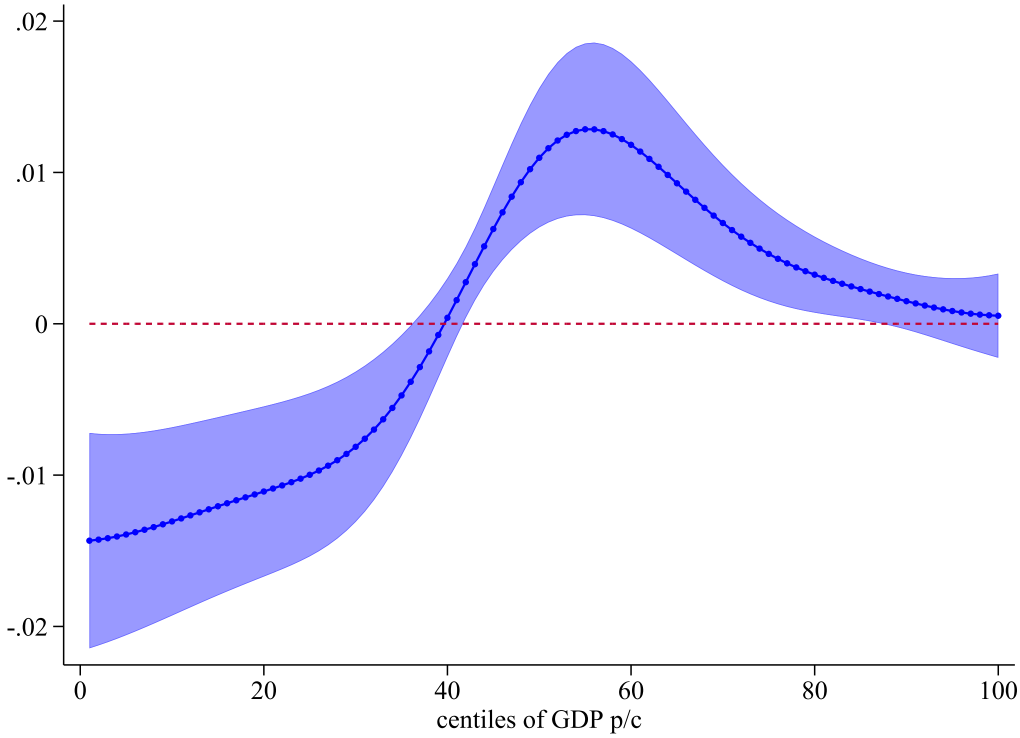
Notes: This figure plots the effect of the initial entry into a foreign destination estimated locally at a given percentile of the ex-ante productivity distribution. The dependant variable is the number of citations. We use Gaussian weights with a bandwidth set to 15 centiles. 90% confidence interval are presented. Standard errors are clustered at the link level.

increased competition it induces for potential innovators in that country (see Aghion et al., 2005): as a result, the impact of the French firm's entry on citations by firms in the destination country may even turn negative. On the other hand, if firms in the destination country are neck-and-neck with the French firm, then these firms can easily build upon the French firm's technology to generate new innovations: in that case entry by the French firm should increase citations by the destination country of the firm's innovations. Finally, if firms in the destination country are far ahead of the French firm's technology, then these firms will often not find it useful to develop further the French innovation as they already enjoy a better technology: entry by the French firm would then have little to no impact on its citations by firms in the destination country.[5]

[5] All these developments should have different consequences for the destination firms' products as well, but the lack of data on those products prevents us from assessing such impacts. They also bring about different consequences for the French exporter's products, which we plan to investigate in future work.

To test for a differential impact of entry on citations varying with a destination's development level, we run a similar version of our static specification described above. But we now allow for our coefficient to vary across the percentiles of the destinations' GDP per capita. At low levels of GDP per capita (below the 40th percentile), entry decreases citations (Figure 10). At intermediate-high level of GDP per capita (between the 40th and the 90th percentile), entry increases citation. And the effect dissipates at higher levels of GDP per capita.

Figure 10: Development and Spillovers



Notes: This figure plots the effect of the initial entry into a foreign destination estimated locally at a given percentile of the per capita GDP. The dependant variable is the number of citations. We use Gaussian weights with a bandwidth set to 15 centiles. 90% confidence interval are presented. Standard errors are clustered at the link level.

4 Robustness

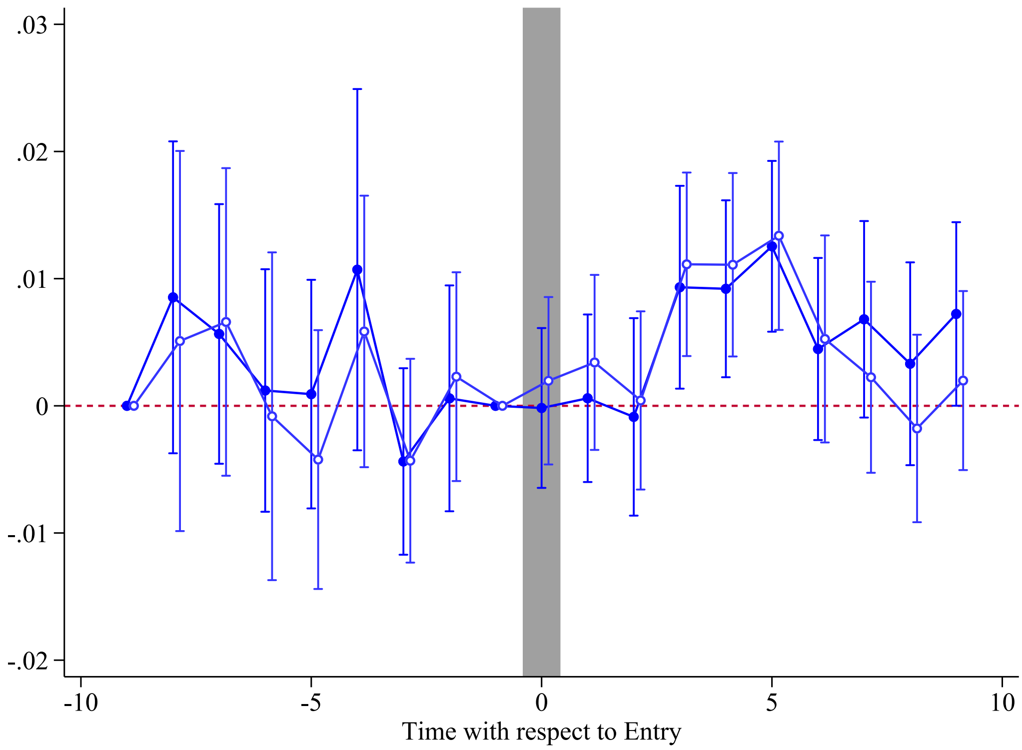
We now report several robustness tests. We first consider departures from our baseline specification, before turning to placebo tests.

4.1 Departing from our baseline specification

4.1.1 Size of the bins

When constructing the iso-probability bins, we face a trade-off between increasing the number of observations per bin and a better approximation of randomness for the timing of entry. Choosing a larger bandwidth for the entry probability provides a higher number of observations per bin but makes each entry within a bin less random (because we cannot control for selection differences within bins). In the baseline specification, we used relatively narrow iso-probability bins representing centiles. As a robustness test, we replicate our regression analysis using bins based on deciles. We find that our results remains qualitatively unchanged (cf. Figure 11).

Figure 11: Different Size of Bins

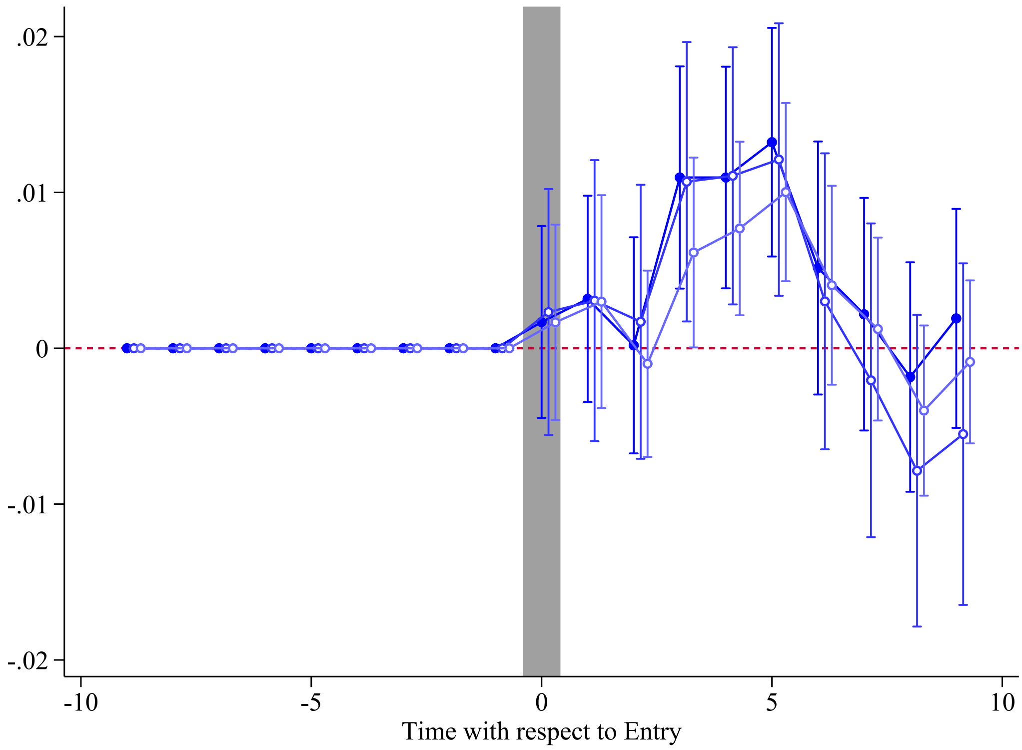


Notes: This figure shows the coefficients from the estimation of our baseline Equation 2 with two different size of iso-probability bins. Here the dependant variable is count of priority citations. 95% confidence interval are presented. Standard errors are clustered at the link level.

4.1.2 Treatment

In the baseline specification, treatment refers to entry, regardless of the continuation or not of exports in the destination in the following years. So the firm is assigned back to the control group for the years post-entry. We can test two polar cases: first the firm remains treated forever after entry, and second the observations following the exit of the market are dropped. We find that doing so does not affect our qualitative findings on the dynamic effect of entry on citations (Figure 12).

Figure 12: Different Definition of Entry

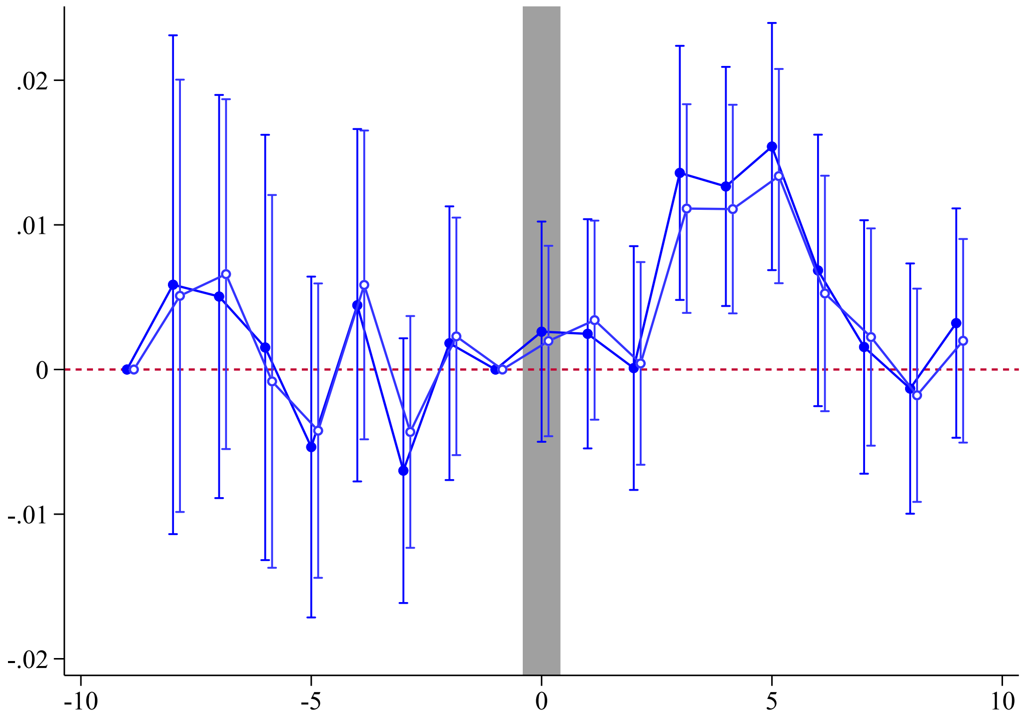


Notes: This figure shows the coefficients from the estimation of our baseline Equation 2 with three different definition of entry. The dark blue line is the baseline definition, the medium blue one corresponds to the case where we drop formerly treated links, the light blue one corresponds to the case where links remain treated even after the firm exit from the market Here the dependant variable is count of priority citations. 95% confidence interval are presented. Standard errors are clustered at the link level.

4.1.3 Sample

A large number of patents receive only very few citations over their life-cycle. We find that our main findings are robust to dropping these patents from our sample (see Figure 13)

Figure 13: Removing zombie patents

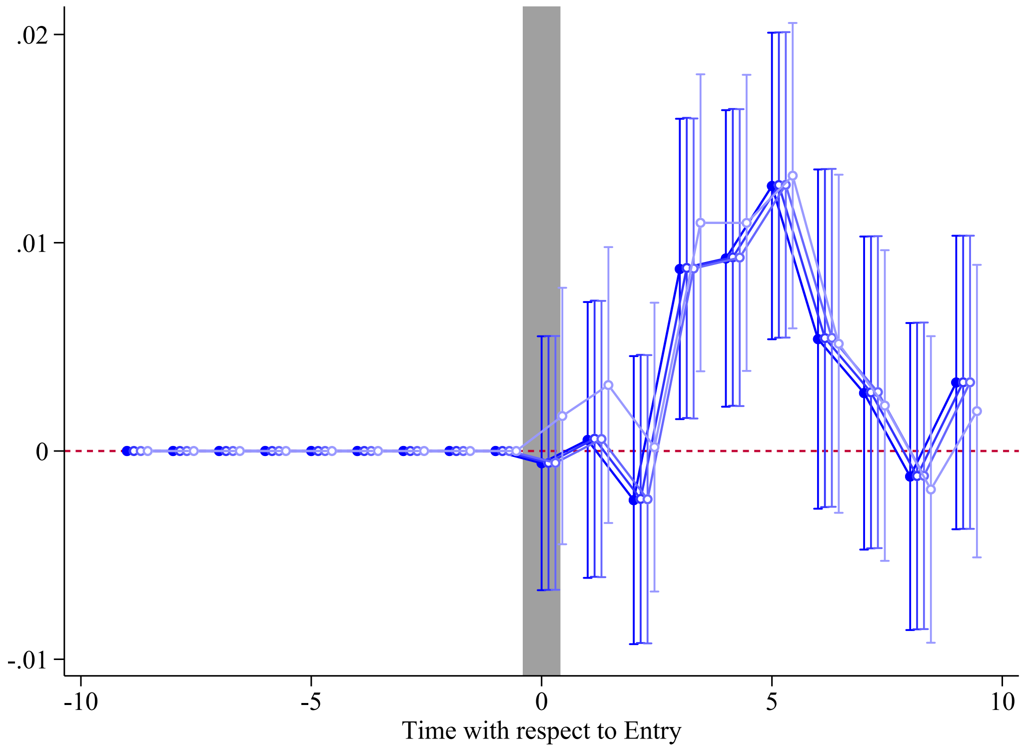


Notes: This figure shows the coefficients from the estimation of our baseline Equation 2. The dark blue line corresponds to the estimation without zombie patents, the light blue line to the baseline sample. Here the dependant variable is count of priority citations. 95% confidence interval are presented. Standard errors are clustered at the link level.

4.1.4 Other control variables

We estimate the baseline semi-dynamic specification with different set of control variables (see Figure 14). Each line is a specification that includes a different set of control variables. It includes at most: the lagged number of citations of the patent, a dummy variable indicating the year the patent was filled, the natural logarithm of the lagged number of employees of the firm and the natural logarithm of the lagged labor productivity. We find that the pattern and overall treatment effect remains stable regardless of the control variables used. The median value of the overall estimated treatment effect across the different specifications is 0.0471 with a minimum of 0.0385 and a maximum of 0.0477).

Figure 14: Sensitivity to different control variables



Notes: This figure shows the coefficients from the estimation of our baseline Equation 2. The dark blue line corresponds to the estimation without zombie patents, the light blue line to the baseline sample. Here the dependant variable is count of priority citations. 95% confidence interval are presented. Standard errors are clustered at the link level.

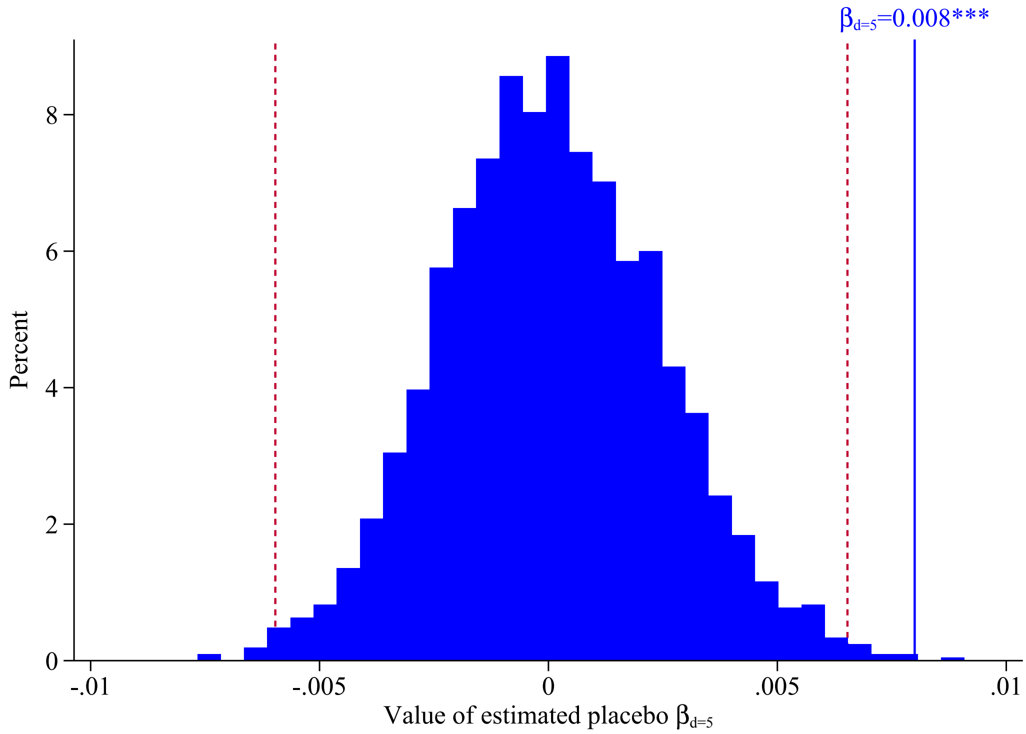
4.2 Placebo tests

In the baseline specification, we clustered standard errors at the firm-country link level. This provided us with standard errors that are asymptotically robust to serial auto-correlation for the error term as well as to correlations across patents within a link. Here we implement Chetty et al., 2009's non-parametric permutation test of $\beta_k = 0$ for $k = \{5\}$

To do so, we randomly reassign the date of entry into an export destination across links and then we re-estimate the second-stage regression. We repeat this process 2000 times in order to obtain an empirical distribution of *placebo* coefficients $\hat{\beta}_k^p$. If entry had no effect on citations, we would expect our baseline estimate to fall somewhere in the middle of the distribution of the coefficients of the placebo coefficients $\hat{\beta}_k^p$. Since that test does not rely on any parametric assumption regarding the structure of the error term, it is immune to the over-rejection of the null hypothesis highlighted by Bertrand et al., 2004.

We plot the histogram of this distribution of placebo coefficients in Figure 15. The figure confirms that our coefficient of interest $\hat{\beta}_{d=5}$ (the solid blue line) lies on the right of the [p0.5,p99.5] interval (the red dashed lines) of the distribution of placebo coefficients. It confirms that initial entry into a destination leads to an increase in citations.

Figure 15: Main Specification: Priority Citations Count



Notes: This figure shows the coefficients from the estimation of our baseline Equation 2. 95% confidence interval are presented. Standard errors are clustered at the link level.

4.3 Alternative windows of estimation

So far, we have assumed that the date of the first entry as observed in the custom data is the first true year of export into that destination. Here, we relax this assumption. To do so, we define new sample periods and different windows of lags and leads.

The first test corresponds to a fully dynamic specification on a sample between 1999 and 2010 testing the impact on citations of entry up to 8 years before the citations occur (and with 4 leads of entry to test for pre-trends). We present the results in Figure 16a. This figure shows a similar pattern as our baseline results, with no evidence for a pre-trend and a positive impact at years 3 to 5 (although less precisely estimated).

The semi-dynamic specification, which includes back 2011 and 2012 and reduces the number of estimated coefficients, provides a similar picture (Figure 16b). The overall treatment effect is 0.0424 compared to 0.0497 in the baseline (see section 3.1).

These results are robust to the change in the measure of citations (Figures 16c, 16d, 16e, 16f). The only noticeable difference with the baseline results is the intensive margin response (see 16f), which appears more persistent than in the baseline specification.

We then repeat the last test with different combinations of the control variables. We present the results in Figure 17. We find that the estimated coefficients remains stable to all these changes in the regression specification.

4.4 Alternative identification strategy

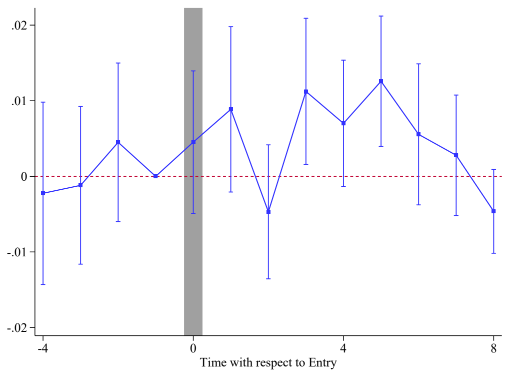
In our baseline model, we identified the effect of entry on citation within a bin of similar firms in a given destination. However, it is also possible to identify the effect within firm but across the destinations of its export portfolios. We therefore estimate the following equation :

$$Y_{p(f),j,t} = \sum_{\substack{k=k_{min} \\ k\neq -1}}^{k_{max}} \beta_k \times ENTRY_{f,j,t-k} + \delta \times X_{p(f),t_e-1} + \gamma_t \times \gamma_f + \gamma_j \times \gamma_z + \varepsilon_{p(f),j,t}, \tag{3}$$

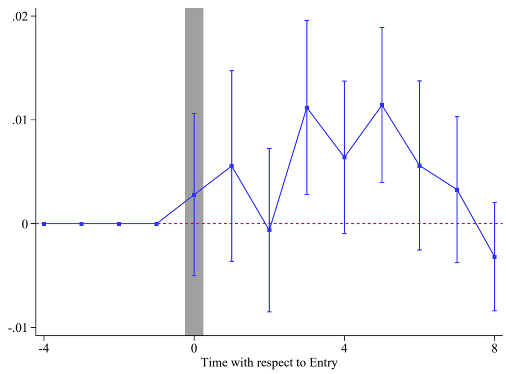
Figure 3 shows the estimated pre-entry and post-entry coefficients for the main variable of interest as well as their 95% confidence intervals. The dependent variable is the flow of priority citations C. On top of the firm$times$year fixed effect, we control for the destination market invariant characteristics by adding a country fixed effect $\gamma_j \times \gamma_z$. We interact it here with the technological field of the patent but omitting this interaction or using the

Figure 16: Alternative Window Specification with alternative LHS variables

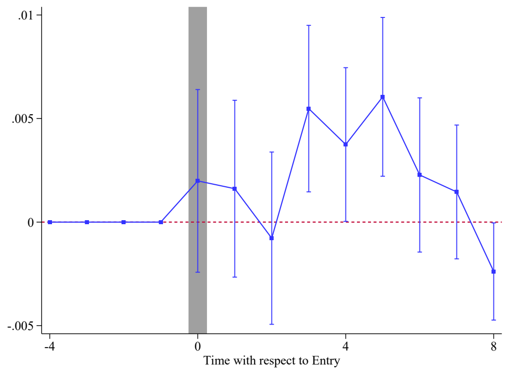
(a) Fully Dynamic: Citations Count



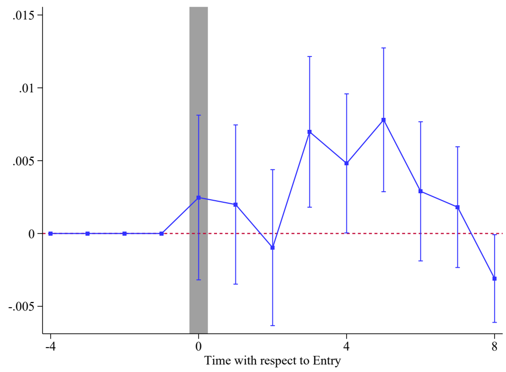
(b) Semi Dynamic: Citations Count



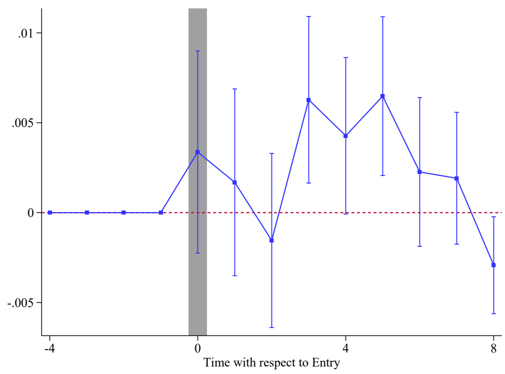
(c) Semi Dynamic: Log(1+Y)



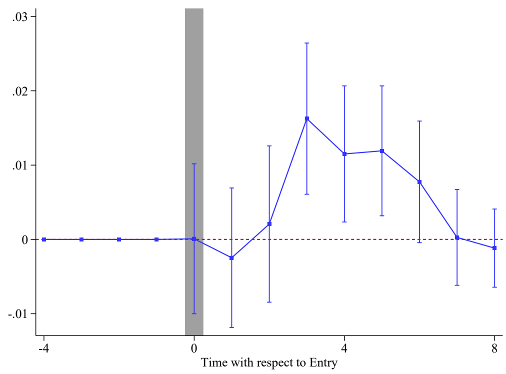
(d) Semi Dynamic: ihs(Y)



(e) Semi Dynamic: LPM

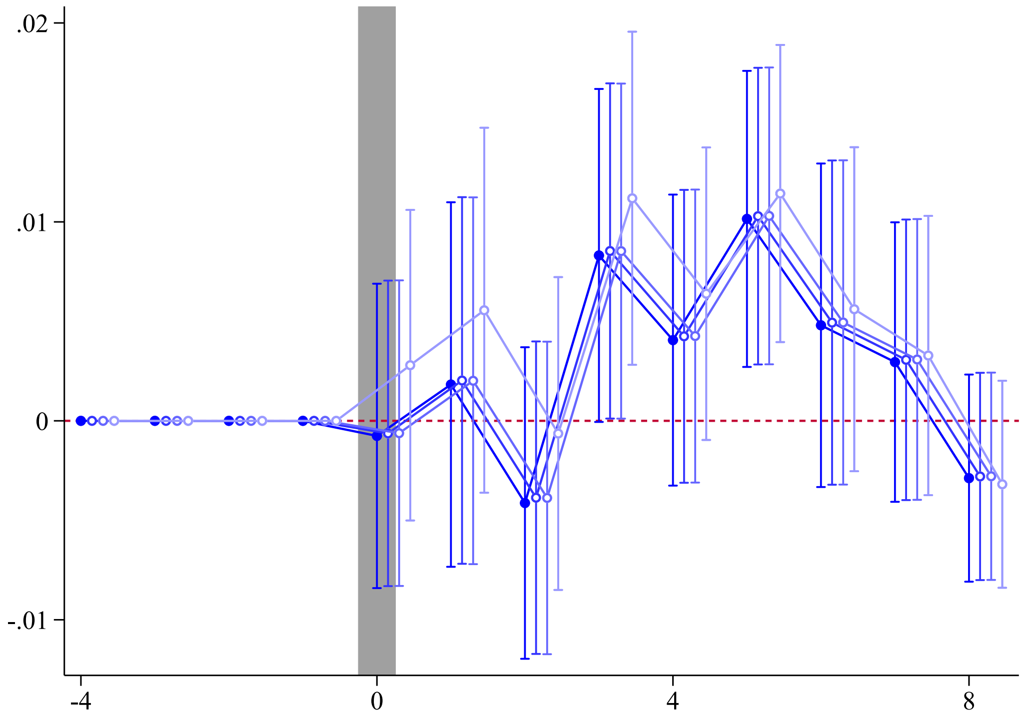


(f) Delta Log Stock of Citations



Notes: This figure shows the estimated $\hat{\beta}$ coefficients from the estimation of our baseline Equation 2. The dependant variable is either the count of priority citations, the log of 1+Citations, the inverse hyperbolic sine of Citations, a dummy variable indicating 1 if the patent is receiving citations, and the delta log of the stock of citations. 95% confidence interval are presented. Standard errors are clustered at the link level.

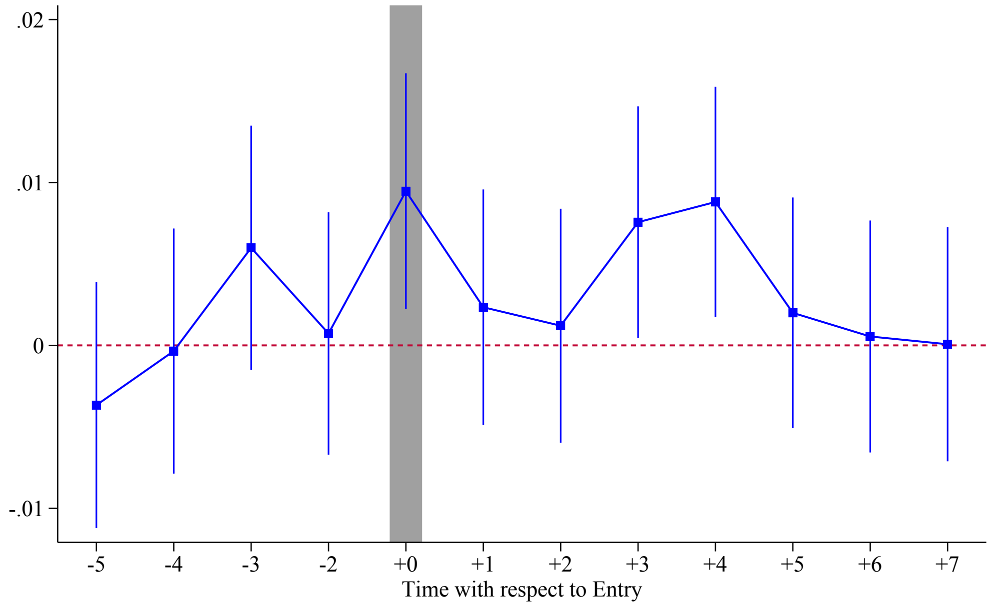
Figure 17: Priority Citations Count with different control variables



Notes: This figure shows the coefficients from the estimation of our baseline Equation 2. The dependant variable is the count of priority citations. Each line represent the coefficients from a regression with a different vector of control variables. 95% confidence interval are presented. Standard errors are clustered at the link level.

firm sector instead does not alter our results. X is a vector of lagged control variable of firm and/or patent characteristics. In this case, it includes the lagged stock of citations ever received by the firm. Once again, the coefficients of the pre-entry dummies fluctuates around zero and are never significant. We then find a positive effect the year of the entry that reverts back to zero for two years before becoming positive and statistically significant again for year three and four following the entry. This effect progressively dies out until the end of the event window.

Figure 18: Priority Citations Count within Firm



Notes: This figure shows the coefficients from the estimation of the Equation 3. The dependent variable is the count of priority citations. Each line represent the coefficients from a regression with a different vector of control variables. 95% confidence interval are presented. Standard errors are clustered at the link level.

5 Discussion and conclusion

In this paper we use French firm-level fiscal, custom, and patent citation data over the period 1995-2012 to estimate the impact of export market entry on the citations of the exporter's prior patents in the destination country. We find a positive and significant effect of entry on those citations. Moreover, we find that this effect is concentrated among the most productive French exporters and in destinations at intermediate levels of development. Overall, our results validate the notion that trade induces technological spillovers (in line with Coe and Helpman, 1995b). And the results are also consistent with Cohen and Levinthal (1989)'s view that spillovers occur conditionally upon the recipient country exhibiting sufficient *absorptive capacity*.

Our findings have several implications. First, our main findings that trade induces knowledge spillovers is in line with the notion that trade is a source of cross-country convergence. Second, fostering development in the destination country increases the country's ability to build upon the innovations brought by foreign exporters. Third, more productive firms – in addition to being more likely to export – are also more likely to induce technological spillovers.

Our analysis can be extended in several interesting directions. We have measured technological spillovers using citations of the exporter's prior patents in a destination. However, one may question whether new patents in the destination country then subsequently lead to an increase in productivity in the destination. If the answer is positive, then this should somehow be reflected in future increases in productivity growth for the affected sectors and destinations that are more highly exposed to entry by innovative firms. This and other extensions of our analysis in this paper are left for future research.

References

Aghion, Philippe and Xavier Jaravel, "Knowledge spillovers, innovation and growth," *The Economic Journal*, 2015, *125* (583), 533–573.

_ , **Antonin Bergeaud, Matthieu Lequien, and Marc Melitz**, "The Impact of Exports on Innovation: Theory and Evidence," NBER Working Paper 24600, National Bureau of Economic Research 2018.

_ , **Nicholas Bloom, Richard Blundell, Rachel Griffith, and Peter Howitt**, "Competition and Innovation: an Inverted-U Relationship," *The Quarterly Journal of Economics*, 2005, *120* (2), 701–728.

Autor, David, David Dorn, Gordon Hanson, Gary Pisano, and Pian Shu, "Foreign Competition and Domestic Innovation: Evidence from U.S. Patents," Technical Report 22879, National Bureau of Economic Research 2016. DOI: 10.3386/w22879.

Azoulay, Pierre, Joshua S Graff Zivin, and Jialan Wang, "Superstar extinction," *The Quarterly Journal of Economics*, 2010, *125* (2), 549–589.

Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan, "How much should we trust differences-in-differences estimates?," *The Quarterly journal of economics*, 2004, *119* (1), 249–275.

Bloom, Nicholas, Mirko Draca, and John Van Reenen, "Trade induced technical change? The impact of Chinese imports on innovation, IT and productivity," *The Review of Economic Studies*, 2016, *83* (1), 87–117.

Bombardini, Matilde, Bingjing Li, and Ruoying Wang, "Import Competition and Innovation: Evidence from China," Technical Report 2017.

Chetty, Raj, Adam Looney, and Kory Kroft, "Salience and taxation: Theory and evidence," *American economic review*, 2009, *99* (4), 1145–77.

Coe, David T and Elhanan Helpman, "International r&d spillovers," *European economic review*, 1995, *39* (5), 859–887.

Coe, David T. and Elhanan Helpman, "International R&D spillovers," *European Economic Review*, 1995, *39* (5), 859–887.

Coe, David T, Elhanan Helpman, and Alexander W Hoffmaister, "International R&D spillovers and institutions," *European Economic Review*, 2009, *53* (7), 723–741.

Cohen, Wesley M and Daniel A Levinthal, "Innovation and learning: the two faces of R & D," *The economic journal*, 1989, *99* (397), 569–596.

Hainmueller, Jens, Jonathan Mummolo, and Yiqing Xu, "How much should we trust estimates from multiplicative interaction models? Simple tools to improve empirical practice," *Political Analysis*, 2016, pp. 1–30.

Jaravel, Xavier, Neviana Petkova, and Alex Bell, "Team-specific capital and innovation," *American Economic Review*, 2018, *108* (4-5), 1034–73.

Keller, Wolfgang and Stephen R Yeaple, "Multinational enterprises, international trade, and productivity growth: firm-level evidence from the United States," *The Review of Economics and Statistics*, 2009, *91* (4), 821–831.

Lequien, Matthieu, Martin Mugnier, Loriane Py, and Paul Trichelair, "Linking patents to firms: insights with French firms," 2019.

Lileeva, Alla and Daniel Trefler, "Improved Access to Foreign Markets Raises Plant-Level Productivity… for Some Plants," *Quarterly Journal of Economics*, 2010, *125* (3), 1051–1099.

Waldinger, Fabian, "Peer effects in science: Evidence from the dismissal of scientists in Nazi Germany," *The Review of Economic Studies*, 2011, *79* (2), 838–861.

Watzinger, Martin, Lukas Treber, and Monika Schnitzer, "Universities and Science-Based Innovation in the Private Sector," 2018. mimeo LMU Munich.

_ , Markus Nagler, Lukas Treber, and Monika Schnitzer, "Mobility of Scientists and the Spread of Ideas," Discussion paper series in economics and management 17-22, German Economic Association of Business Administration 2017.